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Abstract

In this work, we analyze production performance of hospital services in Ontario (Canada)~~,~~ by investigating its key determinants. Using data for the years 2003 and 2006, we follow the two-stage approach of Simar and Wilson (2007). Specifically, we use Data Envelopment Analysis (DEA) at the first stage to estimate efficiency scores and then use truncated regression estimation with double-bootstrap to test the significance of explanatory variables. We also examine distributions of efficiency across geographic locations, size and teaching status. We find that several organizational factors such as occupancy rate, rate of unit-producing personnel, outpatient-inpatient ratio, case-mix index, geographic locations, size and teaching status are significant determinants of efficiency.

Key Words: Hospital Efficiency, DEA, Distributional Analysis, Truncated Regression, Bootstrap.

1. Introduction

In this study, we analyze production performance of healthcare services in Ontario province (Canada)– and its key drivers. In Ontario, the costs of all hospital services are covered under the Canada Health Act and are therefore fully funded by the provincial Ministry of Health and Long-Term Care (MOHLTC). Thus, irrespective of sizes, geographic location and teaching status, all hospitals operate under the same financing system and are indifferent to profit rather striving to maximize the quantity and quality of healthcare services as per service accountability agreement between hospitals and local health integrated network (LHIN).[i] Therefore, the main research focus of our study has been to analyze the determinants of efficiency of hospital services considering different geographic locations (i.e., rural vs. urban), size (i.e., small vs. large), teaching status and other key characteristics. The performance measurement across the different groups of hospitals is very important for understanding the utilization of scarce resources. It also provides important information for development of healthcare reforms to improve global funding system while simultaneously promoting quality and efficiency (Goldstein et al., 2002; Griffith et al., 2002; Mannion et al., 2005; Villard et al., 2005; Navarro-Espigares and Torres, 2011; Liu et al., 2012; Mauro et. al., 2013) as well as better accountability among healthcare providers.

For our analysis, we followed the existing classifications of rural vs. urban, small vs. large, and teaching vs. non-teaching hospitals used by the MOHLTC, the public funder of all hospital services. The concept of a rural hospital, however, is generally defined by several components, including, but not limited to, population size and density, geographic and professional isolation and lifestyle factors. Small hospitals are normally located in rural areas, and rural hospitals tend to be smaller than urban hospitals. A small hospital in Ontario is defined by multiple criteria, including hospital activity, expected stay index (ESI), referral population size and whether it acts as a single provincial community provider (see JPPC, 1997). Teaching hospitals provide both acute and complex patient care and are affiliated with a medical or health sciences school, involved in significant research activity and provide training for interns and residents.[ii]

The performance analysis in this study is based on production theory in economics, where one can determine the extent of resource utilization by estimating the production frontier and considering hospital services provision as a production process where inputs (e.g., nurses' hours, staffed beds, etc.) are transformed into different outputs (e.g., inpatient and outpatient volume). For empirical estimation, we used the data envelopment analysis (DEA) estimator along with both the non-parametric kernel-based density estimation method and truncated regression with double-bootstrap.

DEA is a frontier estimator based on a linear programming approach and is frequently used for assessing efficiency of a decision making unit (here hospital) relative to the observed best-practice frontier of all other hospitals in the sample.[iii] The main advantage of DEA is that it can relatively easily handle a multi-output and multi-input environment without specifying any functional form of the production relationship.[iv] As the hospital sector produces several types of services using several inputs, estimating hospital efficiency via DEA is appealing and is among the most popular approaches in academic literature.

For our analysis of DEA-estimated efficiency scores, we apply the test of Li (1996, 1999) adapted to DEA by Simar and Zelenyuk (2006), with bootstrapping, for comparing distributions of efficiency scores across geographic locations, size and status of hospitals.[v] The use of a version of the adapted Li (1996, 1999) test allows us to test the hypothesis of equality of distributions, i.e., whether there are any significant differences in efficiency distributions across geographic locations, size and status. Finally, we applied the two-stage procedure (DEA + truncated regression, bootstrapped) of Simar and Wilson (2007) to examine the determinants of efficiency of hospital services.[vi] In this two-stage approach, we find that several organizational factors, such as rate of unit producing personnel (UPP), occupancy rate, outpatient-inpatient ratio and case-mix index along with either geographic locations and teaching status or size and teaching status are significant determinants of efficiency.

The paper is organized as follows. Section 2 reviews the related works on hospital efficiency in relation to rural/urban location, size and teaching status. Section 3 presents a theoretical framework of the methods applied for estimation. Section 4 describes the data sources and variables used in the analysis. Section 5 discusses the results of truncated regression analysis, and Section 6 provides concluding remarks.

2. Related Works

Although a large number of studies are available on hospital efficiency analysis (e.g., see Goldstein et. al., 2002; Hollingsworth, 2003; O'Neill et al., 2008; Garcia-Lacalle and Martin, 2010; Rosko and Mutter, 2011 and references cited therein), there are only a handful of studies that focus on identifying the determinants of hospital efficiency (e.g., Grosskopf et al., 2004; Lee et al., 2008; Blank and Valdmanis, 2010; Tsekouras et al., 2010; Cristian and Fannin, 2013; Ding, 2014). Table 1 briefly summarizes some of these studies. In our study, we focus on analyzing hospital efficiency by taking into account geographic locations (urban vs. rural), size (small vs. large), teaching status and other organizational factors that may influence hospital efficiency.

Due to differences in location, size and status, different hospitals face different sets of challenges even though they may provide similar types of services. Rural hospitals provide core medical services such as emergency care, obstetrics and newborn services as well as medical and surgical services of relatively low complexity (Hart et al., 1990; Moscovice & Rosenblatt, 1985). Despite a relatively low demand, hospitals in rural areas in Ontario must maintain minimum staffing levels to be able to provide core services. The rural hospitals on average usually have fewer beds and lower occupancy rates compared to their urban counterparts (Cleverly, 1989a; 1989b). A lower occupancy rate may potentially have a detrimental effect on the efficiency of rural hospitals as the operating expense per adjusted discharge may be greater at a lower rate of occupancy (Oliveira and Bevan, 2008).

Table 1. Selected recent research in hospital efficiency analysis

Authors	Method	Sample	Inputs	Outputs
Grosskopf et al., (2004)	DEA and Regression analysis	236 teaching hospitals and 556 non-teaching hospitals in the US in 1995	Beds, FTE MD, FTE RN, FTE PN, FTE RES, FTE Others	No. of Inpatients, Surgeries, Outpatient/ER
Kontodimopoulos et al. (2006)	DEA	17 small-scaled Greek hospitals for 2003	Doctors, Nurses, Beds	Patient admissions, Outpatients, Preventive medicine services
Lee et al. (2008)	DEA and Multiple regression analysis	106 acute care hospitals in Seoul for 2004	Number of beds, doctors and nurses	No. of Inpatients and Outpatients visits
Blank and Valdmanis (2010)	DEA second stage with bootstrap	69 Dutch hospitals for 2000	Staff and admin. personnel, Nursing personnel, Paramedical personnel, Other personnel, Material supplies	Discharges and First time visits
Garcia-Lacalle, and Martin (2010)	DEA and Multidimensional Scaling	27 Andalusian Health Service (SAS) Hospitals in Spain for 2003 and 2006	Beds, Physicians, Nursing staff	Outpatients visits, Emergencies, Stays, Diagnoses, Operations

Cristian and Fannin (2013)	DEA second stage with bootstrap	Unbalanced panel data set of Critical Access Hospital in the US for the period 1999–2006	Full time equivalent (FTE) personnel and staffed and licensed beds	Outpatient visits, admissions, post-admission days, emergency room visits, outpatient surgeries, and total births

Despite their many disadvantages, rural hospitals were found to be performing as well as or even better than hospitals in urban areas in terms of technical efficiency and quality of services (Nayar and Ozcan 2008). Athanassopoulos and Gounaris (2001), for example, reported that the overall efficiency in urban hospitals was lower than that in rural hospitals (0.75 compared to 0.83). The above findings are consistent with those of Gruca and Nath (2001), who, from a study of 168 hospitals in Ontario, found that rural hospitals were more efficient than those in urban areas (0.77 compared to 0.72). Rural hospitals with smaller bed capacities might be more disadvantaged, and the social aim of ensuring access to medical care for remotely situated populations may override efficiency considerations (McNamara, 1999).

On the other hand, even for hospitals located in rural areas, efficiency can improve with size. This is illustrated in several studies. For example, Kerr et al. (1999) and McCallion et al. (1999) in Northern Ireland reported that larger hospitals were more efficient than smaller units. Furthermore, Athanassopoulos and Gounaris (2001) reported for the case of Greece that small hospitals were found to be the least efficient (0.80) in comparison with medium-sized (0.86) and large (0.90) hospitals. In contrast with the above findings, Gok and Sezen (2013) noted that for the case of Turkey, small hospitals are relatively more efficient and have higher patient satisfaction compared to medium and large hospitals. They further noted that the treatment process in large hospitals might be more complicated as some of these hospitals fall under the category of teaching hospitals, which signifies an imperfection of outcome measurement attributed to lower technical efficiency.

As such, in addition to location and size, another important dimension that affects hospital efficiency is its teaching status. In hospital efficiency analysis, teaching status has also been considered as a structural measure of quality (Rosko and Mutter, 2011). The significance of the teaching hospitals is that in addition to providing direct patient care, these hospitals also act as a source of training for medical students. In this reality, inefficiency can be attributed to the congestion of medical students (Grosskopf et al., 2001a). Another study, Grosskopf et al. (2001b) noted that almost 90% of teaching hospitals perform more poorly than non-teaching best practice hospitals even after eliminating inefficiencies relative to their own frontier. Further to this, they noted that medical school affiliation and accreditation are positively related with teaching dedication and teaching intensity and as such are negatively related to efficiency (Grosskopf et al. (2004). Using second stage regression, Burgess and Wilson (1998) also found that there is no significant difference in technical efficiency across teaching and non-teaching hospitals.

From the above discussion, one can see that different studies present contrasting views of hospital efficiency performance across these three distinct groups of hospitals. This is possibly due to differences in methodological approaches or differences in the countries and/or in the data. However, it is also evident that inefficiency differs across different groups of hospitals, and these differences in performance could be due to a variety of factors.

3. Methodology

To facilitate our measurement of hospital efficiency, we assume that the technology of producing hospital services, i.e., producing an output vector $y \in \mathbb{R}_+^M$, from an input vector $x \in \mathbb{R}_+^N$, can be mathematically characterized by technology set Ψ defined in general terms as:

$$\Psi = \{(x, y) \in \mathbb{R}_+^N \times \mathbb{R}_+^M : \text{x can produce y}\}. \quad (1)$$ [vii]

It is to be noted that many if not all of the inputs that hospitals use can be considered as fixed in a short run, and given these inputs, hospitals are expected to maximize their output of healthcare services. On these grounds, an adequate efficiency measurement would consider the extent to which outputs can be expanded without altering the quantity of inputs.[viii] Thus, a convenient tool for characterizing the production relationship Ψ and, in particular, for measuring efficiency of hospital service production is the Farrell-type output oriented technical (in)efficiency measure, defined for a hospital j with input-output allocation $\left(x^j, y^j\right)$ as

$$TE\left(x^j, y^j\right) = \sup_{\theta}\left\{\theta>0 : \left(x^j, \theta y^j\right) \in \Psi\right\}. \tag{2}$$

In practice the true Ψ is unobserved and is usually replaced with its DEA estimate, Ψ, given by

$$\begin{aligned}\Psi = \Big\{\left(x, y\right) : & \textstyle\sum_{k=1}^{n} z_k y_m^k \geq y_{m,} \quad m = 1,\ldots,M, \\ & \textstyle\sum_{k=1}^{n} z_k x_i^k \leq x_{i,} \quad i = 1,\ldots,N, \; z_k \geq 0, \, k = 1,\ldots,n\Big\}.\end{aligned} \tag{3}$$

where $z_k \geq 0 \left(k = 1,\ldots,n\right)$ are the intensity variables over which optimization (2) is made jointly with optimizing over $\theta \geq 0$, for a given sample $\left\{\left(x^k, y^k\right) : k = 1,\ldots,n\right\}$ of input-output allocations of hospitals.

For the second stage, we assume the true relationship between efficiency and a hospital's characteristics is given by,

$$TE_j = Z_j\delta + \varepsilon_j, \qquad j = 1,\ldots.,n, \tag{4}$$

where Z_j is a (row) vector of firm-specific variables discussed above for each firm j that we expect to influence the (in)efficiency score TE_j through the vector of parameters δ, together with statistical noise, ε_j.[ix] For the estimation of this model, we followed Algorithm 2 of Simar and Wilson (2007), where we replace the unobserved regressand TE_j by its bias-corrected estimate TE_j^{bc}

obtained using DEA with bootstrap incorporating an empirical analogue of (4) given by

$$\widehat{TE}_j^{bc} \approx Z_j\delta + \epsilon_j, \qquad j=1,\ldots,n \tag{5}$$

where we assume $\epsilon_j \sim N(0, \sigma_\epsilon^2)$ such that $\epsilon_j \geq 1 - Z_j\delta,\ j = 1,\ldots,n$ to take into account the truncation issue. This model is then estimated using a maximum likelihood estimator and the inference on coefficients is made based on bootstrap incorporating the structure given in (5). See Simar and Wilson (2007) for further details and required assumptions on the data generating process.

4. Selection of Variables and Data

We used balanced panel data from 113 acute-care hospitals in Ontario for the years 2003 and 2006. Data for this study was obtained from the healthcare indicator tool (HIT), from the Ministry of Health and Long-Term Care (MOHLTC) and the Canadian Institute for Health Information acute-care discharge abstract database (CIHI-DAD). Data from both sources are subject to quality audits.

We followed the same hospital classifications (i.e., rural[x] vs. urban, small vs. large and teaching vs. non-teaching) as those used by the Ministry of Health and Long-Term Care (MOHLTC). In our sample, hospitals located in both rural and suburban areas are considered rural hospitals.

Table 2. Descriptive Statistics of Inputs and Outputs used in DEA

	Variables	Mean	Median	St. Dev
	Administrative Staff Hours	51,404	19,491	70,943
	Nursing Hours	697,488	216,287	986,419
	Staffed Beds	66,952	26,174	81,843
INPUTS	Medical-surgical supplies costs	5,561,858	799,543	9,660,250

	Non-medical supplies costs	5,919,556	1,726,989	8,915,605
	Equipment Expenses	5,758,295	1,526,354	8,903,298
	Ambulatory Visits	111,266	44,692	155,277
OUTPUTS	Case-mix weighted Inpatient Days	82,020	25,315	124,171

Based on the recent literature summarized in section 2 and the availability of data on Ontario hospitals, we adopt the similar hospital production model described in Table 2. Specifically, as an output category, we used 'case-mix adjusted weighted inpatient days' and 'ambulatory visits'. In Canada, the Case Mix Groups methodology[xi] was designed to identify clusters of acute-care inpatients with similar clinical and resource-utilization characteristics. This methodology adjusts for various factors—such as patient age, sex and comorbidities (the number of conditions a patient has beyond the primary reason he or she was admitted into a hospital)—to account for how they may influence the costs of hospital stays.[xii] A similar grouping has not yet been carried out for ambulatory visits. Inputs are classified into three different categories: (1) human resources, including nurses and administrative workers measured in FTE hours; (2) purchased services and supplies, including medical/surgical supplies and non-medical/surgical supplies measured in dollars; and (3) the number of staffed beds and equipment expenses (i.e., measured in dollars) as a measure of capital.

In the second stage of analysis, we examined potential determinants of efficiency through truncated regression with bootstrapping (following the approach of Simar and Wilson (2007)). Along with dummy variables for geographical locations (i.e., urban =1, and rural =0), size (small =1, and large =0) and teaching status (teaching =1 and 0 otherwise), we conditioned on other variables that are perceived as important factors for health care performance, and tested their significance. We presented the descriptive statistics of Z variables in Table 3. Overall, we have used six inputs and two outputs in the DEA analysis and eleven Z variables in the truncated regression analysis.

By pooling the data over time, we implicitly make an assumption that the technology has not changed over the study period. While this assumption would hardly be true if the time lag was substantial, in our case the lag was small, and as such it could be viewed as a simplifying assumption that helped to increase the sample size substantially. In this respect, we also noted there was an important structural change of the healthcare services in Canada, including Ontario. Specifically, the government launched Phase 1 of Surgical Capacity Investments program to reduce the wait times, from the last quarter of the FY2003/2004 to FY2004/2005 and so a big internal restructuring was required during this periods to comply with new provincial wait-times initiatives. Again, in May 2005, Phase 2 allocations were introduced with the largest increase in a decade for some categories of services including hip and knee replacements, and MRI scans (Ontario, 2005). This is also one of the reasons we think the period FY2002/2003 (hereafter 2003) and FY2005/2006 (hereafter 2006) that we use is particularly interesting to investigate if there is any evidence of significant efficiency change during this restructuring and we do this by including a time dummy in the second stage of analysis.

Table 3. Descriptive statistics of Z variables

Variables	Description and unit of measures	Mean	Median	Std. Dev.
OCCUPANCY	Rate of bed occupancy, %	0.85	0.87	0.14
EQUIPMENT	The proportion of equipment expenses (including equipment amortization) attributed to total operating expenses (excluding all interdepartmental expenses), (%)	0.07	0.07	0.02
OUTP-INP	Outpatient volume (ambulatory visits) divided by inpatient volume	1.94	1.69	1.09
UPP	Percentage of Unit Producing earned hours of total Management Operational and Support and Unit Producing earned hours	0.86	0.87	0.04
READMISSION	Unplanned admissions to an acute care institution within a defined time period after an initial episode of inpatient care (See CIHI, 2008c), %	0.93	0.84	0.42
CMI	Case-Mix Index	1.19	1.15	0.25
Log (TR)	Logarithm of total revenue of a hospital. It	7.56	7.43	0.61

	measures total operating revenue excluding non-cash revenue and recoveries within the facility			
GEO	Locations dummy variable (1=urban, 0 = rural)	0.53	1.00	0.50
SMALL	Size dummy variable (1=small, 0=large)	0.41	0.00	0.49
TEACH	Teaching dummy variable (1 = teaching, 0= non-teaching)	0.07	0.00	0.26
YD	Year dummy variable (1=2003, 0=2006)	0.50	0.50	0.50

Some Remarks on Practical Application

A few remarks about the practical application of our approach are in order. First, as for any method, the DEA approach is not without limitations. One of them is the 'curse of dimensionality', which is, in a sense, a price paid for being non-parametric. Besides potential impact on the bias of individual estimates (on which we do not focus), the 'curse of dimensionality' is mostly the problem for the power of a statistical test, reflected in the inability to distinguish (i.e., reject) the null hypothesis from the truth, especially when they are very close; and, the larger is the dimension, the lower is the power. (See more discussion and some Monte Carlo evidence on this in Simar and Zelenyuk (2006)). It is to be noted, however, that most of the null hypotheses we tested below are rejected, suggesting that despite the curse of dimensionality, the tests attained enough power to reject, perhaps because the truth is very far (perhaps much further than observed) from the null hypothesis. On the other hand, whenever we could not reject the null hypothesis, it was always likely, and more so with the curse of dimensionality that the truth was not what the null hypotheses stated but rather that there was not enough power (for a given sample) to reject it. To minimize the 'curse of dimensionality', we tried to keep the dimension of DEA model at a minimum that would still make the production model adequate to the context. The resulting dimension of our DEA model (6 inputs and 2 outputs) described in Table 2, is within the norms of DEA practice (e.g., Atici & Podinovski, 2015; Asmild et al., 2013; and Asmild & Pastor, 2010).[xiii] It is important, however, to perform a sensitivity analysis, to verify which conclusions are robust (and which ones are not) with respect to slight variations in DEA specifications.[xiv] For this reason, we also estimated several alternative DEA models where some of the inputs are aggregated or dropped (we refer to them as Models B, C, D as summarized in Appendix, while the main DEA model is referred to as Model A). The conclusions from all other specifications generally confirm the conclusions from the main DEA model described in Table 2 and in this sense the conclusions are generally robust.

The second issue is the assumption of 'separability' that is needed for theoretical justifications of the two-stage approach of Simar and Wilson (2007). Specifically, this assumption requires that the so-called environmental variables, Z, influence the (in)efficiency but not the technology frontier. Verification of this theoretical assumption in reality is also challenging, and it is fraught with practical difficulties, including the curse of dimensionality problem, possibility of sample correlation between elements in Z and in (X,Y) that may be mistakenly picked up by a test as an influence of Z on the technology frontier in relatively small samples, etc. At this stage, to proceed with the analysis we accept the 'separability' assumption as simplifying, relying mainly on heuristic judgement of the production process, and acknowledge it is an important limitation of the current approach that needs to be addressed in the future. A natural stepping-stone for this research would be to adapt the test from Simar and Wilson (2001). Another possible path for addressing this issue is to adapt to a different paradigm that is based on the concept of partial frontiers and conditional efficiency measures.[xv] This approach requires a substantially larger sample than what we have due to the kernel-type smoothing for Z, and so we also leave this for future research.

5. Results and Discussion

The descriptive statistics of estimated efficiency scores are presented in Table 4.

Table 4. Descriptive Statistics of Estimated Efficiency in Ontario Hospitals

	Mean	Median	St. Deviation	Min	Max

Small hospitals	1.38	1.29	0.44	1.00	3.15
Large hospitals	1.33	1.32	0.23	1.00	2.05
Rural hospitals	1.40	1.34	0.43	1.00	3.15
Urban hospitals	1.31	1.30	0.22	1.00	2.05
Teaching hospitals	1.06	1.05	0.07	1.00	1.21
Non-teaching hospitals	1.38	1.33	0.34	1.00	3.15

Upon examining the arithmetic means of DEA-estimated output oriented CRS (constant returns to scale) efficiency scores, we have found that both small and rural hospitals are, on average, slightly more inefficient compared to large and urban hospitals, respectively. Contrary to the literature, we have found that teaching hospitals are, on average, substantially more efficient compared to non-teaching hospitals. Furthermore, small, rural and non-teaching hospitals show higher variability in their efficiency score.

5.1 Analysis of Efficiency Distributions

The density estimates of the distributions of efficiency scores are shown in Figure 1 in the text and Figures 2 and 3 in the Appendix. The results from the Li-test on equality of distributions are shown in Table 5. From both the kernel density estimates and the Li–test, we conclude that the distributions of efficiency are significantly different (with type-I error being approximately 1% or lower) when comparing teaching vs. non-teaching (Fig. 1), rural vs. urban (Fig. 2) and small vs. large (Fig. 3) hospitals.

Table 5. Adapted Li-test results for equality of distributions of efficiency

	Li Test Statistics	Bootstrap p-value	Decision
small vs. large	4.2097	0.001	Reject H_o
teaching vs. non-teaching	5.9993	0.000	Reject H_o
rural vs. urban	6.3497	0.000	Reject H_o

Notes: 1. The test statistics are computed using the Matlab code from Simar-Zelenyuk (2006), with 5000 bootstrap replications and Gaussian kernel.
2. Bandwidth selection is performed via the Silverman (1986) robust rule of thumb;

It is worth emphasizing here that, generally speaking, the test we used is asymptotic in nature and, as suggested by Monte Carlo studies in previous works, it may require fairly large samples to attain enough power to reject the null hypotheses, especially when estimated random variables rather than the true ones are used to infer on the distributions of these true variables (see Simar and Zelenyuk (2006) for more details and discussion of power). In other words, the fact that the test was able to reject the null hypotheses with our relatively low samples strengthens our confidence that these null hypotheses are unlikely to be true, i.e., these different groups of hospitals are very likely to follow different distributions of efficiency.

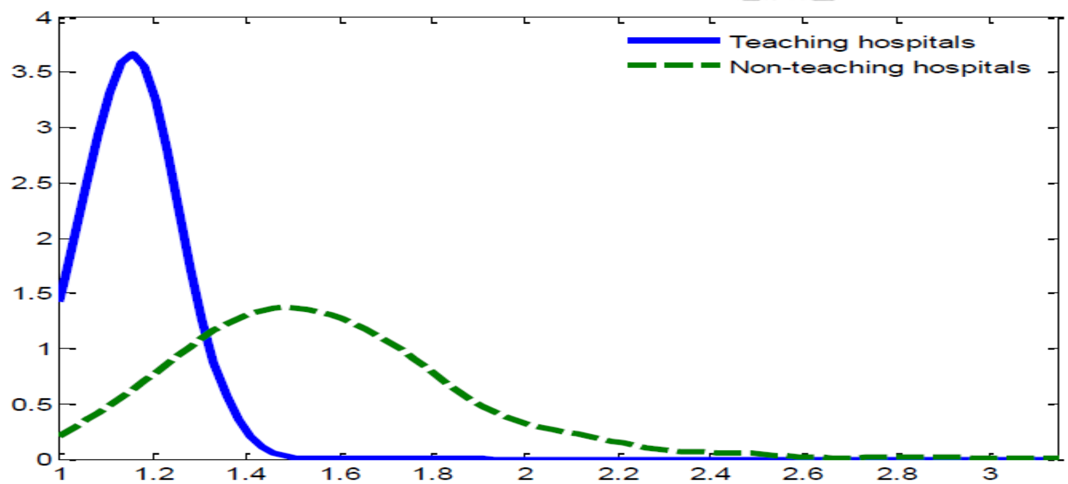

Figure 1. Density estimates of efficiencies across teaching vs. non-teaching hospitals

5.2. Analysis of Determinants of Efficiency through Bootstrapped Truncated Regression

Here we investigate determinants of efficiency scores considering such organization-specific factors as occupancy rate, outpatient-inpatient ratio, rate of equipment expenses (as a proxy of non-price competition), rate of unit producing personnel (UPP), readmission rate (as a proxy of quality), case-mix index and a year dummy along with other characteristics of hospitals such as teaching status, size and geographic locations (see section 4 and Table 3 for more details). It needs to be mentioned here that if a factor is positively (negatively) associated with efficiency, in our case the coefficient will be negative (positive) as we followed an output-oriented approach which produces an efficiency score of greater than or equal to one.

Table 6a. Summary of Results from Truncated Regression with Bootstrap[xvi]

	Model A1	Model A2	Model A3	Model A4	Model A5	Model A6	Model A7
CONSTANT	5.82***	5.46***	6.84***	6.95***	6.92***	6.83***	6.92***
OCCUPANCY	-2.41***	-2.39***	-2.33***	-2.37***	-2.32***	-2.36***	-2.37***
EQUIPMENT	5.27***	5.49***	5.17***	4.88***	5.16***	5.08***	4.86***
OUTP-INP	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***
UPP	-2.20***	-2.16***	-2.30***	-2.31***	-2.28***	-2.25***	-2.42***
READMISSION	0.06	0.06	0.04	0.03	-	0.03	0.04
CMI	-1.15***	-1.12***	-1.15***	-1.14***	-1.16***	-1.13***	-1.13***
Log (TR)	0.13***	0.16***	-	-	-	-	-
GEO	0.02	-	0.05	-	-	-	0.11***
SMALL	-0.01	-	-0.09**	-0.12***	-0.11***	-0.12***	-
TEACH	0.10	-	0.17**	0.16**	0.18**	0.15***	0.14**
YD	-0.03	-	-0.04	-0.04*	-0.04	-	-
σ_ϵ^2	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
Log Likelihood	86.29	85.19	82.18	91.31	80.65	90.52	95.55
Wald χ^2	326.21	250.82	302.45	278.95	216.7	281.03	301.37
AIC	-146.59	-152.39	-140.35	-160.61	-141.30	-161.04	-171.10
BIC	-102.12	-121.60	-99.31	-122.99	-107.10	-126.84	-136.89

Notes:
1. ***,**, *, represent 1%, 5% and 10% level of significance, respectively.
2. The regressand is the bias-corrected (via bootstrap) DEA estimate under CRS.
3. Estimation is according to Algorithm 2 of Simar and Wilson (2007) with 2000 bootstrap replications.

Regression results are presented in Table 6a and Table 6b. In Table 6a, we start from a general model, Model A1, where we have included all hypothesized explanatory variables that we believe may affect the efficiency score of a healthcare services provider. We checked the multicollinearity of the explanatory variables through variance inflation factor (VIF) from collinearity diagnostics (see Tables 10a and 10b in the Appendix). From Table 10b one can see that the VIF are fairly small suggesting that the model does not suffer from problems of multicollinearity. Both tables (i.e., Table

6a and 6b) also present the log-likelihood values for each model, the Wald statistics[xvii] (for hypothesis that all slope coefficients are zero), the AIC and BIC for each model that help us in selecting the simplest parsimonious model. Specifically, we tried different models by eliminating the insignificant variables, which did not substantially change the estimated coefficients of the other variables.[xviii] While doing so, we also compared the log-likelihood values and the AIC and BIC criteria, searching for a model where all or most variables are significant, with among the highest likelihood and among the lowest AIC and BIC values. With this procedure, we conclude that Model A6 and Model A7 fit the data best among the considered models. We will therefore limit our discussion primarily to the results of these two models.

An important conclusion from our regression analysis is that OCCUPANCY is a significant driver of efficiency on average and ceteris paribus (the sign of the coefficient is negative and significant in all the models). This finding is consistent with Zuckerman et al., (1994) and Goldstein et al., (2002) who also found that occupancy rates are inversely related to inefficiency. Similarly, Ferrier and Valdmanis (1996) also concluded that higher occupancy rate and a higher outpatient to total patient ratio helped enhance (cost) efficiency. In this respect, it is also worth noting here that Ontario has the highest hospital occupancy rates of industrialized countries and within Canada, and has the fewest hospital beds per capita of all of the provinces (OHC, 2011). In terms of production theory, hospitals with greater occupancy rates are likely to have occupancies that meet their targeted service capacity as per the accountability agreement, and those with lower occupancy rates have occupancies that are less than their targeted service capacity (see Chang (1998) for discussion of a related hypothesis).

With the fewest beds per capita of all of the provinces, along with highest occupancy rates, there is a question of hospital overcrowding (OHC, 2011), which in turn may imply that inpatient bed cuts would be offset, at least partially, by a shift in services from inpatient to outpatient services (or to the community or other institutions). We, therefore, use the outpatient-inpatient ratio to learn about its effect on hospital efficiency. We expect that the outpatient-inpatient ratio is positively associated with hospital efficiency. From our estimation, we find that OUTP-INP is a significant driver of efficiency (i.e., negatively associated with the inefficiency), on average and ceteris paribus. This result also provides empirical support for the province's strategy to mitigate the pure cost-cutting measures that adversely cause the re-allocation of resources towards outpatient services.

It has been noticed in the literature that hospitals that are financed through a global budget are likely to differentiate themselves on the basis of non-price attributes (Young et al., 2002; Blank and Valdmanis, 2008) and potentially obtain the most technically advanced equipment because of clinical needs as well as maintaining or improving a hospital's reputation for quality and accessibility to both existing and potential enrollees (Young et al., 2002) irrespective of costs (Blank and Valdmanis, 2008). It has also been argued that an increase in the quality of healthcare is likely to require additional units of input per unit of output, thereby implying lower relative efficiency for higher quality providers (e.g., Fizel and Nunnikhoven, 1992; Chilingerian, 1993; Worthington, 2004). In our study, we also find empirical support for such claims by observing that EQUIPMENT (as a proxy for non-price competition) positively and significantly contributed to hospital's inefficiency, on average and ceteris paribus. This does not mean that the hospitals are over-equipped, it rather suggests that many hospitals with less equipment appear to utilize the equipment they have more efficiently in providing hospital services.

In the healthcare sector, the case-mix index (CMI) is often used to measure the overall severity of illnesses treated by hospitals (see Chowdhury et al., (2014) for a review). Therefore, in line with many other studies analyzing efficiency, we have controlled for CMI to adjust the inpatient volume and then used CMI in the second stage to measure the provider's market power (Simpson and Shin 1998).[xix] Throughout all models, the CMI appears as a significant factor driving efficiency, on average and ceteris paribus. This result supports the hypothesis that a higher CMI, which reflects the ability of a hospital to treat more complex cases, enhances hospital efficiency.

Table 6b. Further Sensitivity Checks for Truncated Regression Analysis

	Model A8	Model A9	Model A10	Model A11	Model A12	Model A13
CONSTANT	5.78***	5.67***	5.56***	6.80***	5.68***	5.78***
OCCUPANCY	-2.40***	-2.40***	-2.40***	-2.31***	-3.23***	-3.26***
EQUIPMENT	5.26***	5.24***	5.37***	5.39***	7.01***	6.80***
OUTP-INP	-0.17***	-0.18***	-0.17***	-0.16***	-0.22***	-0.22***
UPP	-2.19***	-2.21***	-2.20***	-2.22***	-1.64**	-1.68**
READMISSION	0.05	0.05	0.06	-	0.14*	0.13*
CMI	-1.15***	-1.15***	-1.13***	-1.15***	-	-
Log (TR)	0.14***	0.15***	0.16***	-	-	-
GEO	-	-	-	-	-	-
SMALL	-0.02	-	-	-0.11***	-0.20***	-0.20***
TEACH	0.10	0.09**	-	0.16**	-0.60***	-0.59***
YD	-0.03	-0.03**	-0.03	-	0.05**	-
σ_{ϵ}^2	0.04***	0.04***	0.04***	0.04***	0.09***	0.10***
Log Likelihood	86.01	85.90	85.46	79.77	-2.29	-2.71
Wald χ^2	301.86	285.40	251.32	207.18	112.54	108.95
AIC	-148.02	-149.80	-150.92	-141.54	24.58	23.43
BIC	-106.97	-112.17	-116.72	-110.76	58.78	54.21

Notes: 1. ***,**, *, represent 1%, 5% and 10% level of significance, respectively.
2. The regressand is the bootstrap based bias-corrected DEA estimate under CRS.
3. Estimation is according to Algorithm 2 of Simar and Wilson (2007) with 2000 bootstrap replications.

As hospital staffs are categorized into unit producing personnel (UPP) and support (MOS), we expect that the number of UPP staff is an important determinant of efficiency (see McGillis et. al., 2004 for more details). While the primary task of MOS staff is to manage and support the operation of the hospital, the function of UPP is to conduct activities that contribute directly to a hospitals' patient care. Therefore, it is expected that a higher proportion of UPP will lead to a higher quantity (and potentially quality) of services and so, potentially, higher efficiency. Results from all the models provide robust evidence supporting the hypothesis that UPP is a significant driver of hospital efficiency, on average and ceteris paribus.

Another important variable we have considered is READMISSIONS. Hospital readmissions add costs to the healthcare system. Previous studies suggested that approximately 8.5 percent of acute care patients were readmitted to hospitals within the 30 days of their initial discharge (CIHI, 2012; Monette, 2012). As policy makers and researchers consider the readmission rate as an important element of quality care, we believe it is an important variable to control for hospital's care quality and so keep it in all of the models to avoid omitted variable bias problems despite the fact that its coefficient is insignificant in most of the models.

We have also used a log of total revenue [log (TR)] as a proxy of global budget as it has been considered a source of inefficiency in the Canadian hospital sector for its reliance on it as the primary source of hospital funding (see CHSRF & FCRSS, 2010). It has been argued that global budgets can perpetuate inefficient care because they offer little incentive to reduce costs or foster innovation (CHSRF & FCRSS, 2010). In some models (Model A1, A2, A8, A9 and A10), we have found that log (TR) is a significant factor of technical inefficiency; however, we eventually dropped it for two reasons: (i) log(TR) is moderately correlated with other variables, such as OCCUPANCY and READMISSIONS as well as with the dummy variables for both size and locations, and so its influence is partially captured by these variables, and (ii) exclusion of this variable leads to substantially better fit of the data (Model A6 and A7) in terms of log-likelihood, AIC and BIC criteria.

While using variables SMALL (dummy for size) and GEO (dummy for geographical locations) together we have found that GEO is insignificant. On the other hand, variables SMALL and TEACH in Model A6 and variables GEO and TEACH in Model A7 are found to be significant. In this respect, we have noted that while almost all rural hospitals are small in size, not all small hospitals are located in rural areas. That is, there are small hospitals located in the urban areas as well, and so we tried to account for the two classifications (i.e., GEO and SMALL) by looking at different specifications. One can see that it is possible to include both of them (i.e., there is no perfect correlation), but it makes both coefficients insignificant (except for Model A3) due to relatively high correlation. Importantly, inclusion of any one of them leads to similar fit and similar estimates of other coefficients as when including the other one instead, which is an indication of robustness of results, and an implication that the small hospitals, the rural hospitals as well as the non-teaching hospitals tend to be more efficient, on average and ceteris paribus.

Finally, we also controlled and tested for whether efficiency changed over time (relative to the pooled frontier), on average and ceteris paribus, via the year-dummy (YD) and found no evidence of significance of coefficient on YD in any of the specifications we tried.

6. Concluding remarks

In this work, we examined production performance of hospital services in Ontario across geographic locations, size and teaching status and other key variables using a non-parametric DEA technique with bootstrapping and truncated regression. As a method, DEA estimates the best-practice frontier through a direct comparison with units that are peers in resource usages and then calculates the distance to this frontier, e.g., via Farrell-type output oriented efficiency measure, as we have done here. We also utilized non-parametric kernel density estimation to visualize distributions of efficiency for different geographic locations, size and teaching status of hospitals.

In our analysis of the estimated efficiency scores of the hospitals, we started with the version of the Li (1996, 1999) test adapted to DEA, with bootstrap. Using this test, we confidently rejected the null hypotheses of equality of the densities (distributions) of efficiencies across different geographical locations (urban vs. rural), size (large vs. small) and teaching status (teaching vs. non-teaching). We then analyzed how various hospital-specific factors are related to the estimated efficiencies by applying the Simar and Wilson (2007) two-stage semi-parametric procedure, following their Algorithm 2. We find that several organizational factors such as outpatient-inpatient ratio, occupancy rate, the rate of unit producing personnel and the case-mix index are positively associated with efficiency of hospitals. On the other hand, the rate of equipment expense is negatively associated with efficiency of hospitals while the readmissions rate is found to be an insignificant factor for explaining variation in the efficiency. Dummy variables for geographic locations, size and teaching status are all significant determinants of efficiency. In particular, we find that the small hospitals, the rural hospitals as well as the non-teaching hospitals tend to be more efficient, on average and ceteris paribus. To check the robustness of our results, we also performed a sensitivity analysis with respect to slight variations of DEA specifications, including reduction of DEA dimension, and find that the conclusions from other specifications generally confirm the conclusions from our main DEA model.

A natural extension of this study would be to analyze the differences in productivity changes as well as cost efficiency across different hospital groups and size if prices of inputs are available. Another interesting question would be to investigate efficiency of resource allocation in hospital services financed through patient based funding (Health Based Allocation Model), including population characteristics.[xx] We leave these for future research.

One can also allow for different frontiers for different groups, yet this would require a substantial increase in the sample size to ensure that each group has trustable results. This would also require modification of Simar-Wilson methodology that was developed for the case of a common frontier and so this is another natural direction for future research.[xxi] We also acknowledge the limitation of the current approach is the assumption on separability. A natural stepping-stone of this research, therefore, would be to adapt the test from Simar and Wilson (2001) and explore other methods that can circumvent this assumption.

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APPENDIX

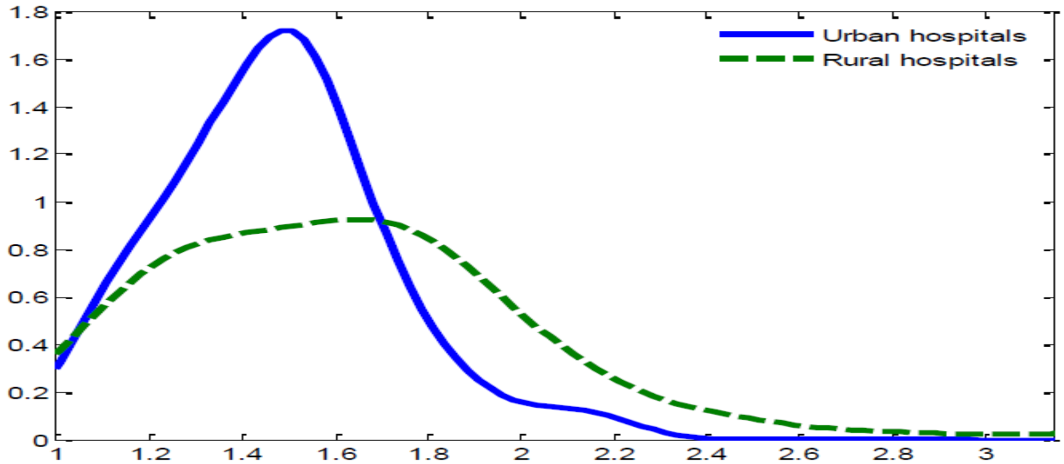

Figure 2. Estimated densities of DEA-estimated efficiency scores: urban vs. rural hospitals

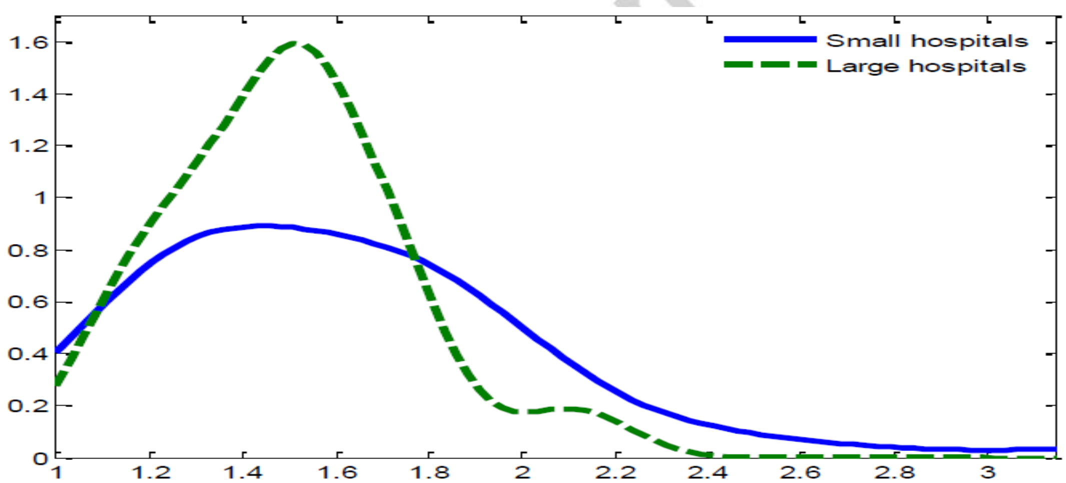

Figure 3. Estimated densities of DEA-estimated efficiency scores: small vs. large hospitals

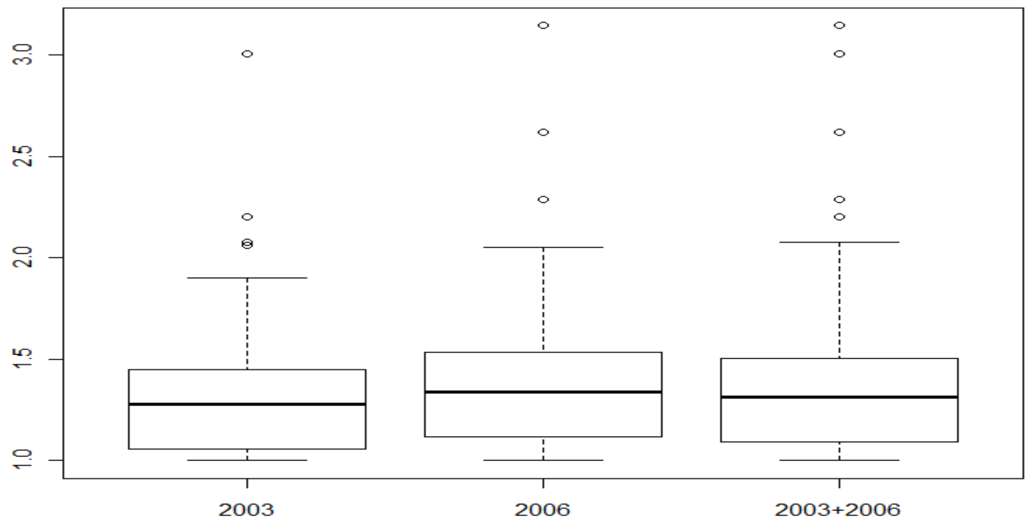

Figure 4. Boxplots of DEA-estimated efficiency scores for different periods

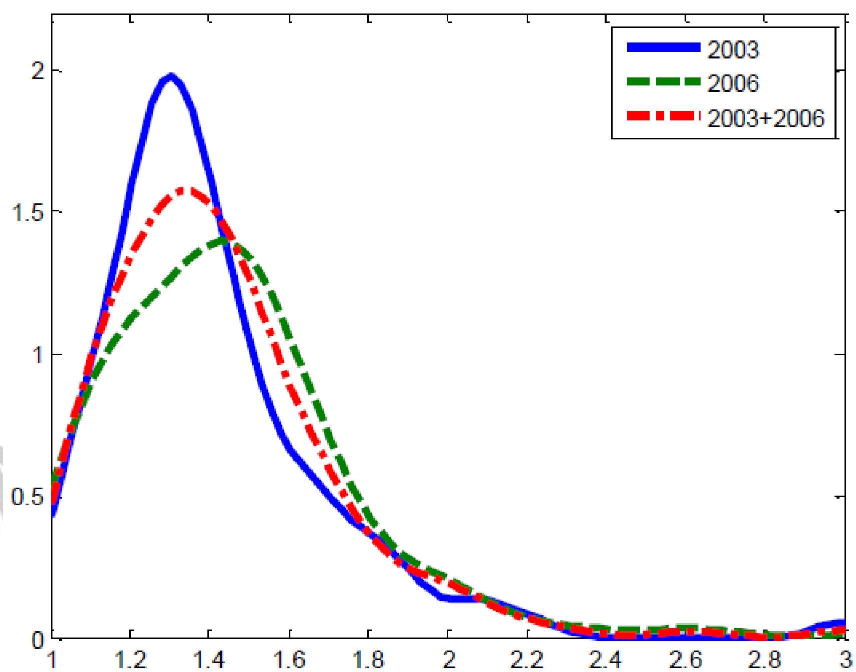

Figure 5. Estimated Densities of DEA-estimated efficiency scores for different periods

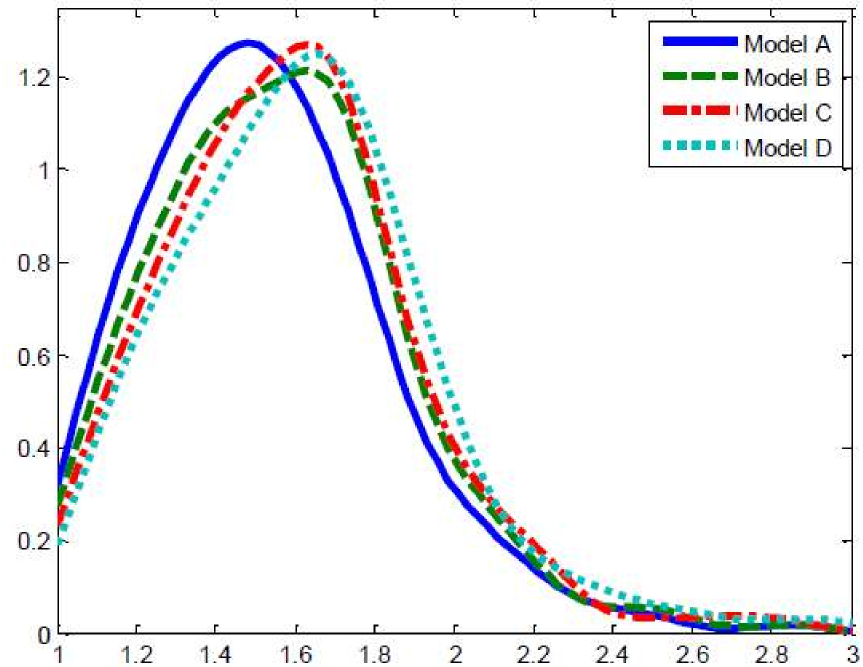

Figure 6. Density of DEA efficiencies under alternative specifications

Table 7. Alternative DEA Specifications

Model Specification / Variables		Model A	Model B	Model C	Model D
Inputs	Nursing Hours	√	√	√	√
	Administrative Hours	√	√	√	√
	Staffed Beds	√	√	√	√
	Medical Surgical Supplies Costs (MSSC)	√			
	Non-Medical Surgical Supplies Costs (NMSSC)	√			
	Equipment Expense (EE)	√	√		
	MSSC+NMSSC		√		
	MSSC+NMSSC+EE			√	
Outputs	Ambulatory Visits	√	√	√	√
	Case-mix weighted Inpatient Days	√	√	√	√

Table 8. Truncated Regression of Model 6 under alternative DEA specifications

Variables	Model B6	Model C6	Model D6
CONSTANT	7.04***	6.83***	6.73***
OCCUPANCY	-2.49***	-2.36***	-2.37***
EQUIPMENT	5.48***	2.75***	1.51*
OUTP-INP	-0.19***	-0.19***	-0.21***
UPP	-2.23***	-1.85***	-1.52***
READMISSION	0.02	0.05	0.05
CMI	-1.16***	-1.18***	-1.21***
SMALL	-0.16***	-0.11***	-0.10***
TEACH	0.20***	0.25***	0.25***
σ_ϵ^2	0.04***	0.03***	0.03***
Log Likelihood	78.88	99.91	100.36
Wald χ^2	253.23	337.83	343.32
AIC	-137.76	-179.82	-180.71
BIC	-103.55	-145.61	-146.51

Notes:
1. ***,**, *, represent 1%, 5% and 10% level of significance, respectively.
2. The regressand is the bias-corrected (via bootstrap) DEA estimate under CRS.
3. Estimation is according to Algorithm 2 of Simar and Wilson (2007) with 2000 bootstrap replications.

Table 9. Li (1996, 1999) –Test Statistics of Equality of DEA Efficiencies

Hypothesis/Models	Test Statistics	Bootstrap p-value	Decision
Model A vs. Model B	0.8503	0.2458	Do not Reject H_0
Model B vs. Model C	0.2454	0.7566	Do not Reject H_0
Model C vs. Model D	0.2670	0.7504	Do not Reject H_0

Notes: 1. The test statistics are computed using the Matlab code from Simar-Zelenyuk (2006), with 5000 bootstrap replications and Gaussian kernel.
2. Bandwidth selection is performed via the Silverman (1986) robust rule of thumb.

Table 10a. Correlation Coefficients between Variables

	Occupancy	Equipment	Outp-Inp	UPP	Readmission	CMI	Log(TR)	GEO	SMALL	TEACH	YD
Occupancy	1.00										
Equipment	-0.13	1.00									
Outp-Inp	-0.24	-0.01	1.00								
UPP	-0.15	-0.07	-0.09	1.00							
Readmission	-0.23	0.10	-0.08	0.18	1.00						
CMI	0.21	-0.04	0.05	-0.21	-0.18	1.00					
Log (TR)	0.51	-0.11	-0.10	-0.27	-0.49	0.26	1.00				
GEO	0.41	-0.12	-0.18	-0.15	-0.46	0.07	0.76	1.00			
SMALL	-0.43	0.14	0.22	0.24	0.41	-0.06	-0.80	-0.77	1.00		
TEACH	0.22	0.06	0.06	-0.16	-0.18	0.48	0.49	0.26	-0.23	1.00	
YD	-0.05	-0.13	-0.13	-0.01	-0.08	-0.10	-0.07	0.00	0.00	0.00	1.00

Table 10b. Variance Influence Factor (VIF)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Occupancy	1.46	1.21	0.69	0.31
Equipment	1.10	1.05	0.91	0.09
Outp-Inp	1.23	1.11	0.82	0.18

UPP	1.17	1.08	0.85	0.15
Readmission	1.46	1.21	0.68	0.32
CMI	1.46	1.21	0.68	0.32
Log (TR)	5.28	2.30	0.19	0.81
GEO	3.03	1.74	0.33	0.67
SMALL	3.95	1.99	0.25	0.75
TEACH	1.83	1.35	0.55	0.45
YD	1.11	1.05	0.90	0.10
Mean VIF	2.10			

Research highlights

- Analyzed productive performance of Hospital Services in Ontario across geographic location, size and teaching status.
- Investigated the determinants of technical efficiency by using the double bootstrap procedure developed by Simar & Wilson (2007).
- Applied non-parametric kernel density estimation to efficiency distribution and utilized the bootstrap based Simar-Zelenyuk-adapted Li-test to make inferences about the distribution of efficiency obtained through DEA.
- Identified several organizational factors such as occupancy rate, rate of unit-producing personnel, outpatient-inpatient ratio, case-mix index, geographic locations, size and teaching status that act as significant determinants of hospital efficiency.

[i] http://www.lhincollaborative.ca/Page.aspx?id=1968, accessed on May 16, 2015.

[ii] http://edrs.waittimes.net/En/Definitions.aspx?view=1, accessed on December 19, 2013.

[iii] See Farrell 1957, Charnes *et al.* 1978, Banker 1993, Färe *et al.* 1994, Seiford and Thrall 1990, etc.

[iv] Multi-input-multi-output cases can also be handled in the so-called stochastic frontier analysis approach, e.g., using polar coordinates transformation as in Simar and Zelenyuk (2011).

[v] A similar approach was undertaken in some other related works, focusing on hospital efficiency (e.g., see Feyrer, 2001; Kumar and Russell, 2002; Henderson and Russell, 2005; Krüger, 2003).

[vi] In a recent survey, Liu et al. (2013) identified the five most active DEA subareas in recent years and among them the ''two-stage contextual factor evaluation framework'' has been found more active. And we thus follow our empirical work using SW (2007), which spawn many new works as seen from the explosive pattern surrounding the paper (see Liu et al. (2013).

[vii] In our formal description we follow Färe and Primont (1995), Simar and Wilson (2007), Simar and Zelenyuk (2006) and Zelenyuk and Zheka (2006) and refer the reader to these works for more details.

[viii] See Charnes *et al.* (1994) pp. 34-39, Jacobs *et al.* (2006) pp. 105-106, Ozcan (2008) p. 23, and Cook et al. (2014) for more discussion on model orientation.

[ix] In general, one could also use non- or semi-parametric estimation at this stage (e.g., as in Park, Simar and Zelenyuk (2008)), but it is not practically feasible in our case due to relatively small sample.

[x] We note that, for simplicity, those hospitals located in sub-urban areas are categorised into rural.

[xi] See Fetter *et al.* (1980), Young *et al.* (1982), Shwartz *et al.* (1984), Klastorin and Watts (1980), Chowdhury *et al.,* (2014) for more details on case-mix measure.

[xii] See Canadian Institute for Health Information (2008a, 2008b).

[xiii] Also see Cook and Tone and Zhu (2014) for related discussions on DEA dimensionality.

[xiv] Here we follow ideas from Zelenyuk and Zelenyuk (2015) applied in the context banking.

[xv] See Badin, Daraio and Simar (2012) and references cited therein for the state of the art on this approach.

[xvi] Estimation for this and other similar tables was done by both Matlab and STATA. We adapted the Matlab code from Zelenyuk and Zheka (2006), with some parts of the code adapted from code of L. Simar.

[xvii] This statistic is for testing the null hypothesis that all the slope coefficients in the model are zero. It is highly significant for all models.

[xviii] We do not claim the insignificant variables are not important (or that we accept the null hypotheses), but rather we do not have evidence to claim that they are significant.

[xix] Note that we use CMI both as adjustment of inpatient days in DEA and as an explanatory variable in the regression, and we model it explicitly in the DEA interrelated with the likelihood of the regression equation in the bootstrap algorithm that corrects for the overall bias. See Chen *et al.* (2006) and Cook *et al.* (2010) for more discussion on shared inputs that can occur in certain two- stage processes. Also see Cook et al. (2014) for relevant discussion about a factor that can play a dual role of input and output simultaneously.

[xx] We thank anonymous referee for this comment.

[xxi] We thank anonymous referee for pointing into this new research direction.