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Data envelopment analysis in the presence of measurement error: case study from the National Database of Nursing Quality Indicators® (NDNQI®)

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Data envelopment analysis (DEA) is the most commonly used approach for evaluating healthcare efficiency [17], and DEA has been used to calculate a composite score for multivariate quality indicators (QIs) [27]. A long-standing concern is that DEA assumes that data are measured without error. This is quite unlikely, and DEA and other efficiency analysis techniques may yield biased efficiency estimates if it is not realized [B.J. Gajewski, R. Lee, M. Bott, U. Piamjariyakul, and R.L. Taunton, On estimating the distribution of data envelopment analysis efficiency scores: an application to nursing homes’ care planning process. Journal of Applied Statistics 36(9) (2009), pp. 933–944; J. Ruggiero, Data envelopment analysis with stochastic data. Journal of the Operational Research Society 55 (2004), pp. 1008–1012]. We propose to address measurement error systematically using a Bayesian method (Bayesian DEA). We will apply Bayesian DEA to data from the National Database of Nursing Quality Indicators® to estimate nursing units’ efficiency. Several external reliability studies inform the posterior distribution of the measurement error on the DEA variables. We will discuss the case of generalizing the approach to situations where an external reliability study is not feasible.

Keywords: healthcare efficiency; simulation; DEA; Bayesian; quality improvement

1. Introduction

Data envelopment analysis (DEA) is the most commonly used approach for evaluating healthcare efficiency [17]. Further, DEA has been used to calculate a composite score for multivariate quality indicators (QIs) [27].

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DEA is attractive for several reasons. It does not require a complete specification of a functional form; it does not require the specification of an error distribution; and it easily handles cases with multiple inputs and multiple outputs.

However, a long-standing concern is that DEA assumes that data are measured without error. This is quite unlikely, and DEA and other efficiency analysis techniques may yield biased efficiency estimates in the presence of measurement error [11,26]. We propose to address the issue of measurement error systematically using a Bayesian method (Bayesian DEA). An important advantage of Bayesian DEA is that it provides a general framework for a ‘stochastic’ view of efficiency studies that can be used with other analytic approaches. Bayesian DEA extends an algorithm of Gajewski et al. [11] in that it accounts for the epistemic uncertainty in measurement error.

We will apply Bayesian DEA to data from the National Database of Nursing Quality Indicators® (NDNQI®) to estimate nursing units’ efficiency and composite QI (multiple input–output DEA). The posterior distribution of the measurement error on all of the variables used in the DEA is informed by data from several external reliability studies. The variables we will consider include staffing levels (for various skills), patient days, patient fall rates, and hospital-acquired pressure ulcer (bedsores) rates. We apply Bayesian DEA and classical DEA to these data and use 95% credible intervals to compare their efficiency scores (composite QIs). We will estimate the impact of ignoring measurement error on classical DEA.

We will discuss the case of generalizing the approach to situations where an external reliability study is not feasible. In this case we discuss the elicitation of prior distributions of measurement error from experts as a promising option. Bayesian DEA provides the healthcare industry (and its stakeholders) unbiased estimates of efficiency and an approach that correctly distinguishes decision-making units (DMUs).

1.1 Motivation

The USA spends nearly twice as much per person on medical care as other developed nations, yet has mediocre health outcomes [1]. Improving healthcare efficiency is vital for the economic well-being of all Americans [30]. Yet to improve efficiency analysts must be able to reliably identify efficient providers or types of care. Unfortunately, the ability of analysts to do so is not clear, as their ability to distinguish differences in efficiency from measurement error is suspect [6]. Measurement error has the greatest potential to produce misleading results when analysts use DEA (the most widely used approach), but the problem affects all forms of efficiency analysis [17].

The impact of measurement error is well known for some statistical methods. For example, consider simple linear regression in which a single dependent variable (y) is regressed on a single predictor variable (x). If y is measured with error it impacts the precision of the regression parameter estimates. This is not really a problem since we can just take more measures. But we still obtain unbiased estimates of the parameter estimates. A more serious issue is when x is measured with error because it causes biased regression parameter estimates. A solution to this problem is to perform an external reliability study for estimating the measurement error for x and then adjust this bias using simulation [2].

1.2 Our question

The important goal of measuring healthcare efficiency via DEA is complicated because there are multiple inputs and multiple outputs. So it is not clear how the precision and/or the bias are affected. Therefore, in this paper we wish to address the following question: ‘Can we reliably estimate healthcare quality and more specifically efficiency?’ We will address this question with data from the NDNQI. Our approach extends the methodology that focuses solely on regression [5].
1.3 Outline

In Section 2 we provide background on hospital report cards with a focus on the NDNQI database. We indicate that not only is DEA useful for estimating healthcare efficiency, it can be used for benchmarking. In Section 3, we provide a review of several studies of nursing efficiency. This provides a basis for the rational of our choice of variables for our efficiency case study using the NDNQI data. We discuss the measurement error issues in the NDNQI and report the reliability of our variables used as inputs and outputs into the DEA. In Section 4 we describe classical DEA algorithm and supply an extension that adjusts for measurement error using Bayesian principles. In Section 5 we provide details of the results of the case study. In general, an external reliability study may not be feasible, so we discuss what to do in this case in Section 6. We provide concluding remarks in Section 7.

2. Background on hospital report cards and NDNQI dataset

Since 1998, the NDNQI has been providing hospitals report cards that are indicators of nursing unit’s quality of care. Starting with 23 hospitals in 1999, it has grown to over 1800 hospitals housing over 17,000 nursing units. Data are entered via a secure website and the NDNQI gives back benchmarking reports to each of the hospitals for them to understand how they are doing on nursing QIs relative to their peers. Hospitals mainly use the information from these reports for quality improvement purposes, for example, implementing new fall risk assessment procedures or preventing pressure ulcers.

The types of reports considered at NDNQI include univariate reports [12] as well as multivariate (i.e. composite indicators) [9]. Rather innovatively, Shwartz et al. [27] consider using DEA for healthcare report cards. They argue that a DEA approach is a benefit-of-the-doubt approach for calculating a composite measure of quality. Therefore, it is our contention that DEA be used for both measuring healthcare efficiency and healthcare quality report cards. However, before applying DEA to NDNQI, we need to choose input and output variables that are appropriate for application to nursing data. A brief review of the literature will elucidate our model development.

3. Review of nursing units’ efficiency studies and choice of variables

Data and measurement issues for efficiency analysis require careful preparation. Coelli et al. [7] mention two important steps, establishing the (1) micro-DEA approach and (2) macro-DEA approach. The micro-DEA approach refers to actually choosing the algorithm after the variables are chosen. For example, constant returns to scale or variable returns are common options. We will choose the classic Charnes–Cooper–Rhodes (CCR) approach [8]. The more important decision is the macro-DEA, which involves choosing the actual input and output variables that go into the DEA.

Coelli et al. [7] define five general categories of inputs: (1) labor is the most important (e.g. staff hours); (2) capital (e.g. beds, computers, technology); (3) energy; (4) materials; and (5) purchased services. Energy, materials, and purchased services are usually collapsed into an ‘other’ category. In our case we will see that labor, such as nursing staff, is our key input variable. In the healthcare industry, it is much more complex to correctly define outputs [14]. To understand the difficulty, consider an industry that has tangible goods (e.g. number of computers produced). It is very easy to count the output here. In healthcare, we can count the number of patient days, but need to attach some measure of the quality of care.

In Table 1 we list several nursing-focused hospital efficiency studies from 2006 to 2010. We have tabulated each of the studies in terms of unit of analysis, input variables, and output variables. All of the studies were at the hospital level of measurement except one which was at the nursing...
unit level (although had only 30 units). All of the studies included nursing labor with one broken down into registered nurse hours per patient day ($X_1$), licensed practical nurse hours per patient day ($X_2$), and unlicensed personnel hours per patient day ($X_3$). Some of the studies also included physicians and dentists. Capital examples included counts of beds and equipment specific to the problem (e.g. dialysis machines). One study had operating expenses, usually a hidden piece of information in hospital data. The outputs varied from values that were not quality specific (e.g. number of tests) to outputs that are measures of nursing quality specific (fall rates, satisfaction, etc.) and case mix index adjusted.

For our study, most similar to Mark et al. [23], we define inputs and outputs from the NDNQI data. First, for inputs we have solely nursing labor: registered nurse hours per patient day (RNHPPD), licensed practicing nurse hours per patient day (LPNHPPD), and unlicensed assistive personnel hours per patient day (UAPHPPD). We have very little capital information at the NDNQI; for example, we do not have the number of beds available to us. For outputs, we focus on nursing related quality: fall rates and pressure ulcer rates. We will appropriately invert them so that they are on a positive scale, necessary for DEA. We address risk adjustment by analyzing unit-level data (e.g. critical care, medical, surgical, combined medical and surgical, and step-down). We will focus on the 1549 combined medical–surgical units that we have complete annual data from latter two quarters of 2009 and first two quarters of 2010 (fiscal year). In Table 2, we summarize the data that goes into these inputs and outputs.
Table 2. Summary of raw variables, indicators, and for NDNQI efficiency study.a

<table>
<thead>
<tr>
<th>Variable</th>
<th>Label</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>RN Hours</td>
<td>$Z_1$</td>
<td>10,838</td>
<td>221,275</td>
<td>46,053</td>
<td>17,941</td>
</tr>
<tr>
<td>LPN Hours</td>
<td>$Z_2$</td>
<td>0</td>
<td>45,755</td>
<td>3399</td>
<td>5380</td>
</tr>
<tr>
<td>UAP Hours</td>
<td>$Z_3$</td>
<td>0</td>
<td>87,856</td>
<td>20,463</td>
<td>10,360</td>
</tr>
<tr>
<td>Patient Days</td>
<td>$Z_4$</td>
<td>1312</td>
<td>24,196</td>
<td>8195</td>
<td>2936</td>
</tr>
<tr>
<td>#Falls</td>
<td>$Z_5$</td>
<td>0</td>
<td>101</td>
<td>29.8</td>
<td>16.2</td>
</tr>
<tr>
<td>#Hospital Pr Ulcers</td>
<td>$Z_6$</td>
<td>0</td>
<td>101</td>
<td>29.8</td>
<td>16.2</td>
</tr>
<tr>
<td>Pts Assessed for PrU</td>
<td></td>
<td>535</td>
<td>91.3</td>
<td>44.3</td>
<td></td>
</tr>
<tr>
<td>RNHPPD (I)</td>
<td></td>
<td>2.43</td>
<td>14.33</td>
<td>5.75</td>
<td>1.39</td>
</tr>
<tr>
<td>LPNHPPD (I)</td>
<td></td>
<td>0.00</td>
<td>4.52</td>
<td>0.43</td>
<td>0.65</td>
</tr>
<tr>
<td>UAPHPPD (I)</td>
<td></td>
<td>0.00</td>
<td>7.06</td>
<td>2.51</td>
<td>0.90</td>
</tr>
<tr>
<td>Fall Rate</td>
<td></td>
<td>1000</td>
<td>0.00</td>
<td>13.34</td>
<td>3.63</td>
</tr>
<tr>
<td>PrU Rate</td>
<td></td>
<td>0.66</td>
<td>1.00</td>
<td>0.97</td>
<td>0.03</td>
</tr>
<tr>
<td>max-Fall Rate (O)</td>
<td></td>
<td>0.00</td>
<td>13.34</td>
<td>9.71</td>
<td>1.59</td>
</tr>
<tr>
<td>1-PrU (O)</td>
<td></td>
<td>0.66</td>
<td>1.00</td>
<td>0.97</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Note: aThere are 1549 units and all are combined medical and surgical. The parenthetical (I) and (O) indicate the form of the variables in input and output form.

4. Developing the Bayesian approach with case study

The aims of this paper are to (1) develop a statistical approach to DEA that incorporates measurement error and (2) apply the Bayesian DEA approach and compare its performance with fixed (classical) DEA. Therefore, we need information about measurement error. Fortunately, we have it since the NDNQI systematically performs reliability studies. Specifically, we desire reliability studies for the DEA inputs ($X$’s) and the DEA outputs ($Y$’s). For the $X$’s, we have reliability studies for the staffing variables [18] and for the patient days [29]. For the $Y$’s, we have reliability studies for the falls [28] and pressure ulcer rates [4,10,15,16].

4.1 Mathematical details of DEA

In the case in which inputs and outputs are measured without error, it is a straightforward linear programming problem to estimate the efficiency scores [8, p. 23]. Using Cooper’s language, for each nursing unit (in general, DMU), Let $i = 1, 2, 3, \ldots, n$. Find the input ‘weights’ ($v_k$) ($k = 1, \ldots, m$) and the output ‘weights’ ($u_l$) ($l = 1, \ldots, s$) such that

$$\max \theta_i = \frac{\sum u_k Y_{ki}}{\sum v_l X_{li}}$$

with the constraint that $(\sum u_k Y_{ki})/(\sum v_l X_{li}) \leq 1$ (for all $i = 1, 2, 3, \ldots, n$), $v$’s $\geq 0$, and $u$’s $\geq 0$. The constraints imply that the ratio of ‘virtual output’ versus ‘virtual input’ should not exceed 1 for every nursing unit. The objective is to obtain weights ($v$’s) and ($u$’s) that maximize the ratio of the nursing unit being evaluated. In the case of $\theta_i = 1$, the nursing unit is ‘fully efficient’, whereas $\theta_i = 0$ identifies a nursing unit that is ‘fully inefficient’.

Classically this framework of DEA is non-stochastic; therefore, if there is no measurement error $\theta_i$ is perfectly measured. But in our case, measurement error in the inputs and outputs will alter $\theta_i$. For the sake of nomenclature, we will call the data measured without error $Y^*$ and $X^*$ for the respective outputs and inputs. We will use reliability studies to obtain posterior distributions of $Y^*|Y, \varphi_1$ and $X^*|X, \varphi_2$ where $X$ and $Y$ are the observed outputs and inputs and $\varphi_1$ and $\varphi_2$ are parameters (technically they are point estimates from these studies) learned from the external reliability studies. Using the posterior distributions of $Y^*$ and $X^*$ we can gain a
posterior distribution of the efficiency scores which we will call \( \theta^*_i | Y, X, \varphi_1, \varphi_2 \), where the ‘*’ helps clearly indicate that data adjusted for measurement error are used to calculate this posterior distribution. This will be very useful for calculating how far off we are in efficiency scores if we ignore the measurement error. For example, we can get the Bias = \( \theta_i - E(\theta^*_i | Y, X, \varphi_1, \varphi_2) \) and Variance = \( \text{Var}(\theta^*_i | Y, X, \varphi_1, \varphi_2) \), whose calculations will be demonstrated via a case study on the NDNQI data. The mean squared error is \( \text{MSE} = \text{Bias}^2 + \text{Variance} \).

### 4.2 Efficiency scores for observed data

For the \( n = 1549 \) medical–surgical units described in Table 2, we calculated each of the nursing unit’s efficiency scores which are displayed in Figure 1. The distribution is slightly skewed to the left and the percentiles of efficiency indicates that 95\% of the efficiency scores are between 0.4255 and 0.9145, the middle 50\% scores are between 0.5604 and 0.7165, and 50\% of the efficiency scores are below 0.6351. Thus, a majority of the nursing units of medical–surgical type are above 50\% efficient.

### 4.3 What about measurement error?

How reliable are these percentiles? This is addressed through the adjustment of measurement error. Some notation is needed to set up the algorithm. Let \( Z_i \) be a vector of data for the \( i \)th nursing unit. Let the input and the outputs for the DEA be \( X_i = f_1(Z_i) \) and \( Y_i = f_2(Z_i) \). Essentially, what we have is reliability studies on \( Z_i \), which after transformation gives us the reliability of the vectors \( X_i \) and \( Y_i \) that go into the DEA. In our medical–surgical units example, we have individual elements as \( Z_1 = \text{RN hours} \), \( Z_2 = \text{LPN hours} \), \( Z_3 = \text{UAP hours} \), \( Z_4 = \text{patient days} \), \( Z_5 = \text{pressure ulcers} \), \( Z_6 = \text{falls} \), and \( n = \text{number of patients assessed} \). Thus, the transformation to inputs and outputs is \( X_1 = Z_1/Z_4 \), \( X_2 = Z_2/Z_4 \), \( X_3 = Z_3/Z_4 \), \( Y_1 = \max -Z_6/Z_4^{1000} \), and \( Y_2 = 1 - Z_5/n \), and max is the maximum fall rate \( (Z_6/Z_4^{1000}) \) across all units.

![Figure 1](image-url)  
Figure 1. The DEA scores using the classical algorithm described in Equation (1) for \( n = 1549 \) medical–surgical units. Key summary statistics: 2.5 percentile = 0.4255, 25 percentile = 0.5604, 50 percentile = 0.6351, 75 percentile = 0.7165, and 97.5 percentile = 0.9145.
Several of the variables in the vector $Z$ have measurement error models on the lognormal scale. Specifically, we use the notation that $Z_j$ is the observed value, $Z_j^*$ is the unobserved true value, and $\varepsilon_j$ is the multiplicative error. The lognormal measurement error model is written

$$\log(Z_j) = \log(Z_j^*) + \log(\varepsilon_j),$$

where we assume that $\log(Z_j^*) \sim N(0, \sigma_{Bj}^2)$ and $\log(\varepsilon_j) \sim N(0, \sigma_{Wj}^2)$; $\sigma_{Bj}^2$ represents the between variance of the log of the latent variable and $\sigma_{Wj}^2$ is the variance of the measurement error of the log of the observed variable. The intraclass correlation coefficient (ICC) under this parameterization is

$$ICC_j = \frac{\sigma_{Bj}^2}{\sigma_{Bj}^2 + \sigma_{Wj}^2} = \frac{\sigma_{Bj}^2}{\sigma_{Tj}^2}.$$  

Using lognormal ratios, it is easily shown that the posterior distribution $Z_j^* | Z_j, \sigma_{Wj}^2 \sim LN(\log(Z_j), \sigma_{Wj}^2),$ (3)

where ‘LN’ is the lognormal distribution. To obtain this distribution, the ‘sufficient information’ for obtaining the posterior distribution in Equation (3) is $Z_j$, ICC$_j$, and $\sigma_{Tj}^2$ (note that $\sigma_{Wj}^2 = (1 - ICC_j)\sigma_{Tj}^2$). Using Equation (3) then we can also calculate the reliability of the ratio of two variables measured with error, for example, suppose we want the true distribution of RNHPPD which is the ratio of the variables for $j = 1$ and $j = 4$, then we obtain

$$\frac{Z_1^*}{Z_4^*} | Z_1, Z_4, \sigma_{W1}^2, \sigma_{W4}^2 \sim LN(\log(Z_1) - \log(Z_4), \sigma_{W1}^2 + \sigma_{W4}^2).$$

(4)

Table 3 shows what we call ‘sufficient information’ for estimating the measurement error for the four $Z$ variables specifically we need total and within variances. As an example, consider a case in which we have a unit that we observe $Z_4 = 5067$ patient days and $Z_1 = 27,958$ RN hours, which results in $X_1 = Z_1 / Z_4 = 5.52$ RN hours per patient day. Using the results in Equations (3) and (4) as well as the ‘sufficient parameters’ in Table 3, we gain the posterior distributions shown in Figure 2.

Rather than the closed-form distributions, one can also use simulation to generate approximations to the posterior distribution. This will be useful later, so we illustrate how to do so on the lognormal examples. Suppose we have $B$ simulations, then one can simulate the $b$th iteration of Equation (3) by simulating

- $\log(\varepsilon_j^{(b)}) \sim N(0, \sigma_{Wj}^2)$, and then
- $Z_j^{*(b)} = Z_j / \varepsilon_j^{(b)}$.

Repeat this expression in Equation (5), say $B = 1000$ times and obtain the kernel-estimated smoothed values in Figure 3, closely resembling the results in Figure 2.

Table 3. With $Z_j$, this is the ‘sufficient information’ for estimating the posterior distribution of $Z_j^*$ and ratios of any.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$j$</th>
<th>ICC$_j$</th>
<th>Study</th>
<th>$\sigma_{Bj}^2$</th>
<th>$\sigma_{Wj}^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(RN hours)</td>
<td>1</td>
<td>0.95</td>
<td>[18]</td>
<td>0.15</td>
<td>0.01</td>
</tr>
<tr>
<td>log(LPN hours)</td>
<td>2</td>
<td>0.93</td>
<td>[18]</td>
<td>16.40</td>
<td>1.15</td>
</tr>
<tr>
<td>log(UAP hours)</td>
<td>3</td>
<td>0.94</td>
<td>[18]</td>
<td>0.44</td>
<td>0.03</td>
</tr>
<tr>
<td>log(patient days)</td>
<td>4</td>
<td>0.94</td>
<td>[29]</td>
<td>0.15</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Figure 2. Consider a case in which we have a unit that we observe \( Z_4 = 5067 \) patient days and \( Z_1 = 27,958 \) RN hours, which results in \( X_1 = Z_1 / Z_4 = 5.52 \) RN hours per patient day. Using the results in Equations (3) and (4) as well as the ‘sufficient parameters’ in Table 3, we gain the posterior distributions shown here.

Figure 3. Repeat this expression in Equation (5), \( B = 1000 \) times and obtain the kernel-estimated smoothed values below, closely resembling the results in Figure 2.
4.3.2 Binomial model 1 (output: pressure ulcer rate)

The basic model for understanding the measurement error for the pressure ulcer rates begins at the individual pressure ulcer and establishing sensitivity and specificity from a survey of pressure ulcer pictures [15,16]. Let $y_i$ be the observed pressure ulcer status for individual $i$. Let $y^*_i$ be the true pressure ulcer status for individual $i$. Then using the reliability study’s point estimates, we estimate the specificity to be $P(y^*_i = 0|y_i = 0) = 0.98$ and the sensitivity to be $P(y^*_i = 1|y_i = 1) = 0.81$. Now convert the individual model to a unit model. First, suppose we observe $Z_5$ pressure ulcers and $n$ patients assessed ($n - Z_5$ patients have no pressure ulcers). Then based on the above model, we can see $U_5^* \sim \text{Binomial}(0.98, n - Z_5)$, the number of false negatives, and $V_5^* \sim \text{Binomial}(0.81, Z_5)$, the number of true positives. Combining this information

$$Z_5^* = (n - Z_5 - U_5^*) + V_5^*.$$ (6)

Using a numerical example, suppose we observe $n = 113$ patients with $Z_5 = 4$ having pressure ulcers (PrU rate = 3.54%). Suppose we have $B$ simulations, then one can simulate the $b$th iteration by simulating $U_5^{*\,(b)} \sim \text{Binomial}(0.98, 113 - 4)$, $V_5^{*\,(b)} \sim \text{Binomial}(0.81, 4)$, and $Z_5^{*\,(b)} = (113 - 4 - U_5^{*\,(b)}) + V_5^{*\,(b)}$. Repeat this expression in Equation (5), say $B = 1000$ times to obtain the histogram in Figure 4.

4.3.3 Binomial model 2 (output: fall rate)

The reliability of falls can be summarized by the famous quote ‘If a tree falls in a forest and no one is around to hear it, does it make a sound?’ (see, e.g. [32]). Unlike pressure ulcer rates, where we know how many patients we did not observe a pressure ulcer, we do not know the

![Figure 4.](https://example.com/figure4.png)

Figure 4. Suppose we observe $n = 113$ patients with $Z_5 = 4$ having pressure ulcers (PrU Rate = 3.54%). Suppose we have $B$ simulations, then one can simulate the $b$th iteration by simulating $U_5^{*\,(b)} \sim \text{Binomial}(0.98, 113 - 4)$, $V_5^{*\,(b)} \sim \text{Binomial}(0.81, 4)$, and $Z_5^{*\,(b)} = (113 - 4 - U_5^{*\,(b)}) + V_5^{*\,(b)}$. Repeat this expression in Equation (5), $B = 1000$ times to obtain this histogram.
number that was not observed to fall. Therefore, our fall rate measurement error model involves sensitivity only [28]. For an individual who was observed to fall, let \( f_i \) be the observed fall status and \( f_i^* \) be the true fall status for individual \( i \). Then the sensitivity is \( P(f_i^* = 1|f_i = 1) = 0.962 \). The model becomes as follows. Suppose we observe \( Z_6 \) falls, then the number of true positives is \( Z_6^* \sim \text{Binomial}(0.962, Z_6) \). Therefore, suppose we have \( B \) simulations, then one can simulate the \( b \)th iteration by simulating

- \( Z_6^{(b)} \sim \text{Binomial}(0.962, Z_6) \), and
- Log-normal model patient days (via Equation (5)).

For example, suppose we observe 10,616 patient days and \( Z_5 = 36 \) falls (fall rate = 3.39). Using Equation (7), simulate true falls and patient days and then report their posterior distributions as shown in Figure 5.

### 4.3.4 A Bayesian approach for estimating DEA accounting for measurement error

By combing the steps above, we obtain an overall methodology that obtains the posterior distribution of \( \theta_i^*|Y, X, \varphi_1, \varphi_2 \).

- Step 0: Set \( b = 0 \).
- Step 1: Set \( b = b + 1 \).
- Step 2: Simulate \( Z^{(b)} \) using the approaches previously outlined (Equations (5)–(7)).
- Step 3: Calculate inputs \( X^{(b)} \) and outputs \( Y^{(b)} \) using \( Z^{(b)} \) from Step 2.
- Step 4: Run DEA algorithm on simulated data (Equation (1)).
- Step 5: Save the efficiency scores for each unit \( \theta_i^{(b)}|Y, X, \varphi_1, \varphi_2 \), for \( i = 1, 2, 3, \ldots, n \).
- Step 6: Go to Step 1 (stop when \( b = 1000 \)).
- Step 7: Summarize.

![Figure 5](image-url)
In the final step we summarize the $p$th percentile with a kernel density estimator, and call that $\theta^{*(p)}_i \mid Y, X, \varphi_1, \varphi_2$. Note that the $p$th value is defined from the distribution of efficiency scores on the observed data. We can also estimate the difference in percentiles, for example, the difference in the 75 percentile and the 25 percentile as $\theta^{*(0.75)}_i \mid Y, X, \varphi_1, \varphi_2 - \theta^{*(0.25)}_i \mid Y, X, \varphi_1, \varphi_2$. To measure global efficiency, we have the posterior distribution estimated as

$$\bar{\theta}^{*(b)} \mid X, Y, \varphi_1, \varphi_2 = \frac{\sum_{i=1}^n \{\theta^{*(b)}_i \mid X, Y, \varphi_1, \varphi_2\}}{n}.$$ 

5. Results of bayesian approach via case study

Figure 6 shows the posterior distribution of the efficiency scores for the 2.5 percentile, 25 percentile, 50 percentile, 75 percentile, and 97.5 percentile and the observed efficiency scores. It highlights the uncertainty in each of these percentiles. The half width of each of these 95% intervals gets larger as the percentile gets larger. The half widths for these percentiles are 0.10, 0.13, 0.15, 0.17, and 0.19, respectively. The biases for these cases are 0.05, 0.05, 0.08, 0.09, and 0.13. These correspond to a mean-squared error of 0.0048, 0.0072, 0.0130, 0.0164, and 0.0257. Figure 7 summarizes the posterior distributions for the differences between 75 percentile and 25 percentile as well as differences between 97.5 percentile and 2.5 percentile. The posterior probability that the 25 percentile is bigger than 75 percentile is $\Pr(\theta^{*(0.75)}_i \mid Y, X, \varphi_1, \varphi_2 - \theta^{*(0.25)}_i \mid Y, X, \varphi_1, \varphi_2 < 0) = 0.1370$, using a 0.05 cut-point, so they are not very different from each other. Conversely, $\Pr(\theta^{*(0.975)}_i \mid Y, X, \varphi_1, \varphi_2 - \theta^{*(0.025)}_i \mid Y, X, \varphi_1, \varphi_2 < 0) < 0.001$; therefore, in the percentiles further out we have detected differences at the 0.05 cut-point.

For overall average efficiency, the half-width is 0.04, the bias is 0.07, and the mean-squared error is 0.0049 (Figure 8).
6. Generalizing the approach to situations where an external reliability study is not feasible

The data from the NDNQI case study allow us to measure error of all of the variables via external reliability studies. However, in general, reliability studies may not be available and too costly to
perform. In these cases, we are in need of estimates of measurement error. In this case we will train experts in the definition of measurement error and build elicitation tools that will inform expert-based estimates of measurement error. For example, recruit six content experts to be interviewed regarding their opinion of the measurement error. Before the interview we would ask them to review relevant literature so that they are familiar with the variables. Then we would continue the interview, for example, we would ask them why the error varies in their population or the targeted item under study. To gage our ability to train we would evaluate the experts’ measurement error on a variable that we might know its measurement error. The iterative process involves: eliciting summaries of experts’ measurement error, fitting a model to these summaries, and assessing the accuracy, and if inadequate repeat the process [24]. This summary for all variables (especially the ones with no external reliability studies) will be used for identifying measurement error to be programmed into Bayesian DEA.

7. Discussion and conclusion

We have demonstrated that we can reliably measure global efficiency. Our proposed methodology for adjusting for measurement error in DEA is broadly applicable. It can incorporate a number of distributions that are non-normal (e.g. lognormal and Binomial). The Bayesian approach via simulation allows for this flexibility. In this paper, we compare Bayesian DEA to classical DEA, but because the Bayesian approach is used to modify the underlying data, the data can be analyzed in a number of ways. Once the modification is complete, the data can be analyzed using stochastic frontier analysis [21], corrected ordinary least squares, or quantile regression. Our approach, therefore, applies to all of the widely used strategies for assessing efficiency.

Our case study focuses on hospitals, but the tools and techniques that we propose here can be fully applicable to other healthcare settings. For example, DEA has been used to study efficiency in nursing homes, health maintenance organizations, and a variety of other settings [22]. In fact, our method is applicable for all activities analyzed with DEA. If measurement error is substantially greater in healthcare than in other activities evaluated with DEA, then the DEA scores estimated with classical deterministic models would be even less reliable.

Our case study indicates that even with ‘substantially reliable’ data, DEA can vary in precision: (1) differences in 2.5 percentile and 97.5 percentile are pronounced; (2) but differences in 75 percentile and 25 percentile not as pronounced. However, this quantification of the measurement error at the efficiency stage guides us in saying what units are truly different. In our view this is a significant discovery. For our data set, we cannot statistically distinguish the DEA scores at the 25th and the 75th percentiles. This finding has big implications about the validity of comparisons of the DEA scores of individual DMUs. For example, for any pair of DMU’s DEA score between the 25th and 75th percentiles, we cannot make any worthwhile evaluation about their comparative efficiencies. Further, we have quantified that the overall estimate of efficiency is biased by .06. Therefore, we can reliably measure efficiency in medical–surgical units up to a point. A current limitation of our approach is that it would be helpful to incorporate full uncertainties of external reliability studies; currently we incorporate only the point estimate.

Our research has motivated two new questions: (1) can we longitudinally estimate health-care efficiency (e.g. stock market)? and (2) can we integrate this approach with the approach of Gajewski et al. [11] and Barnum et al. [3]. Further research will address both questions.

Clearly, DEA is a useful tool for increasing the efficiency of healthcare. Our contention is that it needs to incorporate measurement error. We addressed this by developing a Bayesian DEA approach that adjusts for measurement error. An adjusted DEA allows researchers to have tools for properly assessing the efficiency of hospitals, nursing homes, and many healthcare settings. Regardless of the political climate of healthcare in the next several years, researchers
and policy-makers will want the correct picture regarding the healthcare efficiency in the USA, which is provided by our methodology.

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