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Abstract

In the past decades, hospitals have been facing pressure to increase the efficiency of resource allocation. One way to achieve higher levels of technical efficiency is to treat more patients with the same amount of personnel, which could potentially lead to a trade-off between improving efficiency and maintaining good patient service. The aim of this study is to demonstrate how the nonparametric conditional approach can be used to integrate quality into the analysis of efficiency. The conditional approach allows investigating the mechanism through which quality enters the production process. Generally, an external variable may enter the production process by affecting either the attainable frontier or the distribution of inefficiencies inside the production set. To account for the heterogeneity of hospital services, we focus on a hospital department as the unit of analysis. We use data from 178 departments of interventional cardiology and consider three different measures of quality: patient satisfaction, risk-adjusted mortality, and patient radiation exposure. Our empirical assessment shows that the impact of quality on the production process differs according to the utilized quality measure. Patient satisfaction does not affect the attainable frontier but does have an inverted U-shaped effect on the distribution of inefficiencies; risk-adjusted mortality negatively impacts the attainable frontier at high values of mortality but does not impact the distribution of inefficiencies; and patient radiation exposure is not associated with the production process. Our results refute the existence of a clear trade-off between efficiency and quality. The conditional approach can be applied to deal with the complexity of the underlying relationships between efficiency and quality.

Keywords: quality, efficiency, cardiology department, conditional approach, data envelopment analysis (DEA)

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Introduction

Rapidly growing health expenditures over the recent decades have raised concerns about the affordability of hospital care and have put pressure on hospitals to increase the efficiency of resource allocation. One way to achieve higher levels of technical efficiency is to produce higher quantities of output with the same quantities of input, or in other words, to treat more patients with the same amount of personnel. However, health care providers argue that lowering the ratios of personnel to patient could lead to a deterioration of the quality of health services. To encourage quality improvement, most health care systems introduced various quality assurance programs and some health systems even explicitly relate the remuneration of providers to the achieved results on quality indicators, known as pay-for-performance incentives [1].

While health care policy emphasizes the importance of both efficiency and quality, so far only a small proportion of research analyzing efficiency in the health care sector considered quality. Hollingsworth [2] identified more than 317 publications up to mid-2006 that relied on nonparametric, such as Data Envelopment Analysis (DEA) or Free Disposal Hull (FDH), and parametric, such as Stochastic Frontier Analysis (SFA), methods to estimate and compare the efficiency of health care providers. However, only 9 percent of these publications integrated some measures of quality into the analysis. The paucity of studies accounting for quality is in part caused by the lack of methodological guidance on the integration of quality into the efficiency analysis. We are particularly interested in the nonparametric routes of estimating efficiency and will focus on such throughout this study.

There are three main methods to integrate quality into the efficiency analysis. Thus, some studies treated quality as an additional freely (or strongly) disposable output of the efficiency model [3-11], applying the so-called *one-stage approach* [12]. These studies often performed some transformation to the quality measures in order to represent the idea that more is better for the production of outputs (e.g., mortality rate would be transformed to inverse mortality). Alternatively, other studies included the lack of quality (more is worse) in the efficiency model as an additional weakly disposable output [13-17]. The assumption of weak disposability in these so-called *congestion models* imposes an opportunity cost on the disposal of “bad” outputs [18]. In the health care context, this could mean that reducing mortality rate requires sacrificing the treatment of further patients. The common element of the one-stage approach and the congestion analysis is that quality is used to augment the production set. In contrast to these two approaches, other studies advocated using quality as an external variable, which is not part of the production process, but is helpful in explaining the differences in efficiency across health care providers [19-25]. These studies applied the *two-stage approach* by estimating the values of provider efficiency in the first stage without considering quality and then regressing the obtained efficiency estimates on quality in the second stage of analysis.

The three methods described above rely on rather different assumptions about the channel through which quality influences the production process. Augmenting the efficiency model by adding quality measures to the outputs using either strong (the one-stage approach) or weak (the congestion models) disposability assumptions suggests implicitly that quality has an effect on the attainable set of inputs and outputs. However, this need not be the case, as quality may have an effect on the distribution of the inefficiencies inside the production set without affecting the efficient boundary [26]. In this case, adding quality to the production set would be inappropriate because the new constraint would be binding only for observations with high values of quality (or lack of quality) in relation to inputs [27]. Moreover, the selected efficiency model, such as DEA or FDH, imposes rather restrictive assumptions on the augmented production set, such as disposability, monotonicity, convexity, and returns to scale, which may not be appropriate for the measures of quality [12]. The transformations of the measures of quality to represent either a “good” or a “bad” output may be another source of bias in the efficiency model [28]. On the other hand, the two-stage approach of treating quality as an external variable requires that quality does not have an effect on the attainable set but instead has an effect only on the distribution of the inefficiencies inside the production set [29]. Simar & Wilson [29] described the situation in which an external variable has no effect on the attainable set as a separability condition. This condition may or may not be supported by the data, which necessitates a formal test to avoid a bias in empirical results [30]. Benchmarking decision-making units and examining the underlying relationship between efficiency and quality using the above methods may become problematic when the underlying assumptions are not verified in the empirical settings.

Another important aspect in the examination of the trade-off between efficiency and quality is the variety of measures utilized to capture the quality of provided services. Thus, previous studies relied on the indicators of outcome quality (e.g., mortality rate [3,7,8,10,20], hospital-acquired infections [14,16], and readmissions [17]), process quality (e.g., acute myocardial infarction (AMI) patients who received aspirin within 24 hours of arrival [11]), structural quality (e.g., extra nursing hours [4]), and patient experience (e.g., patient satisfaction [5]) as well as various combinations of multiple quality measures. However, different measures of quality may have a different relationship to efficiency. For example, if a reduction in physician ratios would lead to a reduction in the time spent talking to patients without compromising clinical care, this would most likely result in the negative relationship between efficiency and the measure of quality captured in patient satisfaction, but there may be no relationship between efficiency and clinical measures of quality [31]. Moreover, some utilized measures, for instance, mortality rate for AMI, capture only a part of hospital quality and may thereby not be representative of the total hospital quality but rather reflect the quality of particular hospital departments. In fact, previous research has shown that hospitals performing well on one condition (e.g., congestive heart failure) may not perform as well on other conditions (e.g., pneumonia) [32].

In the context of the above, this study aims to demonstrate the application of an advanced nonparametric method – the conditional approach – which allows exploring the relationship between efficiency and quality while avoiding the limitations of the previous studies. The conditional approach provides a flexible way to integrate quality into the efficiency model without the need to transform the measures of quality and impose additional assumptions, such as disposability, monotonicity, convexity, and returns to scale. Furthermore, the conditional approach is based on the probabilistic formulation of the production process and as such is easily extended to a partial frontier analysis [33]. Estimates based on the partial frontier are no longer deterministic and are thus less affected by extreme values than full-frontier measures, such as DEA or FDH, and have better rates of convergence [33]. Finally, the conditional approach allows differentiating between the two types of the effect of quality on the production process: the effect on attainable frontier and the effect on distribution of inefficiencies [26]. We take advantage of the hospital data at the department level, namely interventional cardiology departments, which ensures that the compared decision-making units rely on similar production technology and provide consistent quality indicators. We examine three different measures to account for the potential differences between quality dimensions. Thus, we examine two measures of clinical quality: risk-adjusted mortality to depict the outcome dimension and patient radiation exposure to depict the process dimension of quality. Moreover, patient satisfaction is used to account for patient experience. This study, therefore, contributes to the existing literature by providing the first empirical application of the conditional approach to the integration of quality into efficiency analysis and analyzing the relationship between efficiency and different measures of quality.

Methodology

The methods for nonparametrical efficiency analysis have been extensively described in Ozcan [34], Simar & Wilson [12] and elsewhere. The conditional approach was formally described in Bădin et al. [35] and references therein. In this chapter, we will provide an intuitive explanation of the main concepts of the conditional approach to enhance the understanding of this advanced method.

Conditional approach

The production technology is described by the vector of inputs $X \in R_+^p$ and the vector of outputs $Y \in R_+^q$. The production set Ψ includes all technically feasible combinations of inputs and outputs: $\Psi = (x, y) \in R_+^{p+q}$, where x can produce y. In their innovative study, Cazals et al. [33] proposed a probabilistic formulation to describe the production process. To obtain robust nonparametric estimates, Cazals et al. [33] suggested estimating the partial efficiency measure of order-m. These robust measures overcome the limitations of traditional nonparametric estimators (e.g., DEA and FDH) of being sensitive to outliers and having low rates of convergence. The empirical estimators are obtained from a sample of n observations. The estimator based on the partial frontier compares a unit (x, y) to m randomly selected peers from the population of units producing more output than y. The order-m output-oriented efficiency measure is given by the following integral:

$$\hat{\lambda}(x, y) = \int_0^\infty (1 - (1 - \hat{S}_{Y|X}(uy|x))^m)\mathrm{d}u, \qquad (2.1)$$

where $\hat{S}_{Y|X}(y|x) = \frac{\sum_{i=1}^{n} \mathrm{I}(x_i \le x, y_i \ge y)}{\sum_{i=1}^{n} \mathrm{I}(x_i \le x)}$ and $I(\cdot)$ is an indicator function, which equals 1 if the condition is true and 0 otherwise. The parameter m represents the number of units used to benchmark performance and determines the degree of robustness of the obtained estimate.

Cazals et al. [33] and Daraio & Simar [36] demonstrated how to incorporate the set of environmental variables $Z \in R^r$ and obtain the conditional measures of efficiency. The attainable conditional production set can be expressed by: $\Psi^Z = (x, y)|Z = z$, where x can produce y. Similar to the unconditional order-m efficiency, the conditional measure of output-oriented order-m efficiency is obtained by solving the following integral:

$$\hat{\lambda}(x, y|z) = \int_0^\infty (1 - (1 - \hat{S}_{Y|X,Z}(uy|x, z))^m)\mathrm{d}u \qquad (2.2)$$

where $\hat{S}_{Y|X,Z}(y|x,z) = \frac{\sum_{i=1}^{n} \mathrm{I}(x_i \leq x, y_i \geq y) K((z-z_i)/h_n)}{\sum_{i=1}^{n} \mathrm{I}(x_i \leq x) K((z-z_i)/h_n)}$, $K(\cdot)$ is some kernel function with compact support and h_n is the observation-specific bandwidth. Bădin et al. [37] showed how to derive the optimal value of the bandwidth.

Bădin et al. [26] explained how the conditional approach can be used to disentangle the channels through which an external factor Z enters the production process. In fact, Z may either affect the range of attainable values (X, Y), causing a shift in the attainable frontier, or it may affect the distribution of the inefficiencies inside the production set with the boundary not affected by Z, or it may affect both. Analyzing the ratios of the conditional to unconditional efficiency estimates, $\hat{R}(x, y|z) = \hat{\lambda}(x, y|z)/\hat{\lambda}(x, y)$, is informative about the potential shift of the attainable frontier due to the influence of Z. In contrast, regressing the conditional efficiency estimates $\hat{\lambda}(x, y|z)$ on Z allows observing the effect of Z on the distribution of the inefficiencies.

Illustration using simulation

To illustrate the main concepts of the conditional approach, we simulate two datasets inspired from Bădin et al. [26] and Bădin et al. [35]. To keep the graphical presentation simple, the amount of input is standardized to one ($X \equiv 1$). Therefore, decision-making units compete on the basis of maximal output Y. The inefficiency term is half-normally distributed $U \sim \mathcal{N}^{+}(0, \sigma_U^2)$ with $\sigma_U^2 = 3$. The external variable Z is uniformly distributed, $Z \sim unif(0,\ 10)$.

The observations ($n = 200$) are simulated according to the following two data generating processes (DGP):

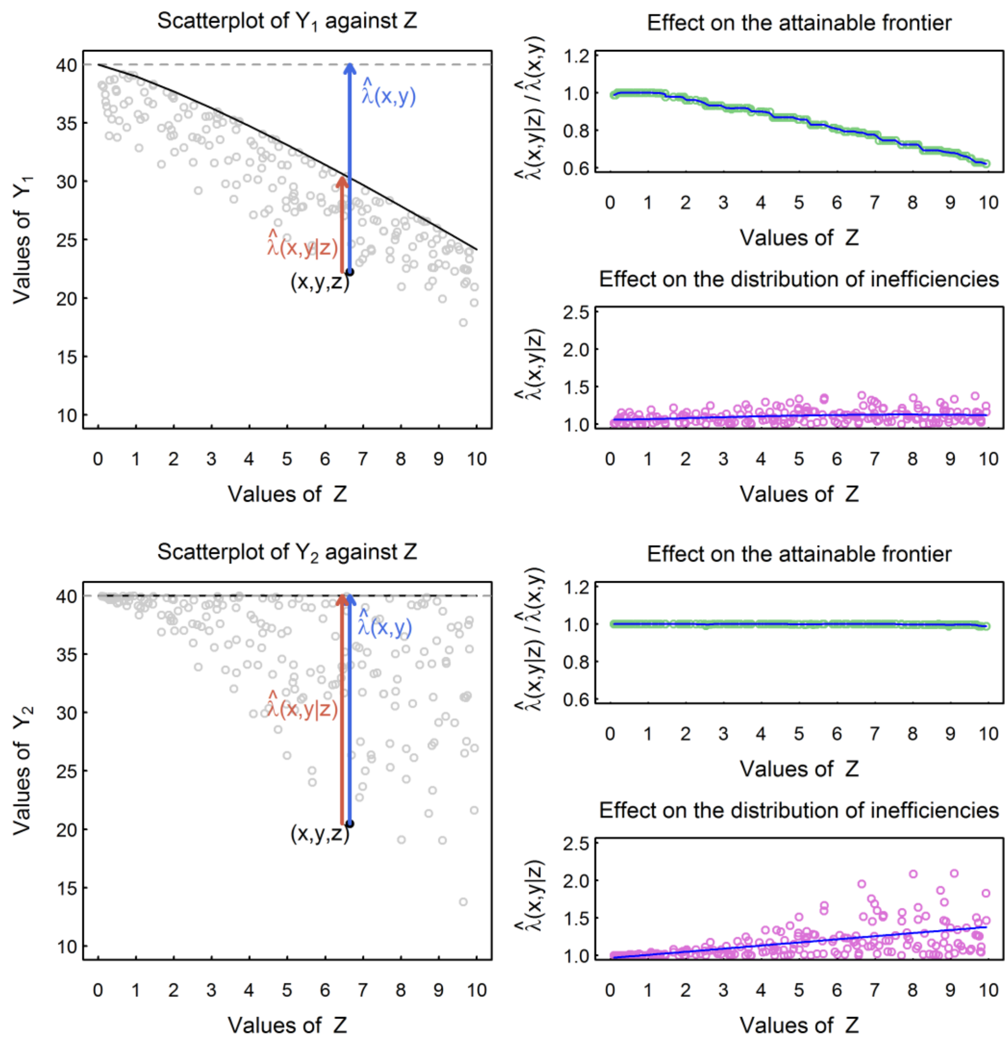
$$Y_1 = 40 - Z^{1.2} - 2U, \qquad (2.3)$$

$$Y_2 = 40 - 0.5UZ^{1.2}. \qquad (2.4)$$

Note that in the first DGP, Z enters the production process by affecting the attainable frontier, whereas in the second DGP, Z affects the distribution of inefficiencies but not the boundary of the attainable set.

The left panel of Fig. 1 illustrates the two datasets resulting from equation (2.3) and equation (2.4). In the upper scatterplot, the effect of Z on the shift of the attainable frontier is observed in the solid black line, which is different from the dashed line representing maximal output in the absence Z. Therefore, the conditional measure $\hat{\lambda}(x, y|z)$, which compares units facing similar level of Z, is different from the unconditional measure $\hat{\lambda}(x, y)$, which does not take Z into account. In the lower scatterplot, Z does not have an effect on the attainable frontier (the solid and dashed lines coincide), leading to the equality of conditional $\hat{\lambda}(x, y|z)$ and unconditional measures $\hat{\lambda}(x, y)$. However, the cloud of data points indicates that the distribution of the inefficiencies is affected by Z, because they tend to be more dispersed at larger values of Z than at smaller values of Z.

Figure 1:



Legend Figure 1: Two mechanisms of the influence of $\mathbf{Z}$ on the production process. In the upper panel, $\mathbf{Z}$ has an effect on the attainable frontier by influencing the output $\mathbf{Y_1}$ directly. In the lower panel, $\mathbf{Z}$ affects the distribution of inefficiencies but does not affect the attainable level of output $\mathbf{Y_2}$.

The right panel of Fig. 1 illustrates how two different nonparametric regressions can be used to explain the effect of Z on the production process. In the first nonparametric regression, the ratios of conditional to unconditional efficiency estimates $\hat{R}(x, y|z) = \hat{\lambda}(x, y|z)/\hat{\lambda}(x, y)$ are regressed on Z to investigate the impact on the attainable frontier. In the second nonparametric regression, the conditional efficiency estimates $\hat{\lambda}(x, y|z)$ are regressed on Z to examine the effect on the distribution of inefficiencies. In the first DGP (the upper panel), Z affects the attainable frontier, therefore, the fitted regression line of $\hat{R}(x, y|z)$ on Z is decreasing, which represents an unfavorable influence of Z on the attainable frontier. In contrast, the regression line of $\hat{\lambda}(x, y|z)$ on Z is flat, because, in the first DGP, the distribution of the inefficiencies is not affected by Z. In the second DGP (the lower panel), Z enters the production process by affecting the distribution of the inefficiencies, but it does not affect the attainable frontier. Therefore, the fitted regression line of $\hat{R}(x, y|z)$ on Z is flat, whereas the fitted line of $\hat{\lambda}(x, y|z)$ on Z is increasing. Because higher values of $\hat{\lambda}(x, y|z)$ represent higher inefficiency, an increasing regression line, in this case, represents an unfavorable influence of Z on the distribution of inefficiencies. Thus, the above illustration provides two examples of the influence of Z on the production process: in the first DGP, Z influences the structure of the attainable frontier relative to which the efficiency of producers is measured and, in the second DGP, Z does not affect the attainable frontier but influences the variation in efficiency between the production units.

Data

We combined data from three sources to obtain structural data on hospital cardiology departments and the corresponding quality measures from calendar year 2012. Structural data on inputs and outputs were retrieved from Structured Quality Reports, which are released annually by all acute care hospitals in Germany [38]. The quality measure of patient experience was obtained from the independent non-governmental agency "Weisse Liste", which conducts the largest nationwide survey of patient satisfaction with roughly a million returned surveys for 2012 [39]. The dataset was supplemented with nationally validated measures of inpatient clinical quality that have to be delivered mandatorily by German hospitals [40].

Two inputs included the number of full time physicians and the number of full time nurses. The output was measured by annual inpatient discharges adjusted for case-mix. To adjust the number of outputs for case-mix, we used the procedure based on the relative length of stay in different diagnostic categories, which was developed by Herr [41] and subsequently applied in empirical applications in the absence of information on Diagnosis-Related Groups (DRG) [42].

We used three quality indicators: patient satisfaction, risk-adjusted mortality, and patient radiation exposure. Patient satisfaction is increasingly accepted as one of the benchmarks of quality in healthcare and has been shown to be consistenly related to clinical effectiveness and patient safety [43]. In our analysis, patient satisfaction was measured as the patient's willingness to recommend the hospital to a best friend. The responses on the Likert scale range from 1 (very likely to recommend the hospital) to 6 (not at all likely to recommend the hospital). We used the mean value across all obtained responses in a cardiology department with a minimum of 30 responses. Higher values of patient satisfaction represent worse department quality.

Mortality rate is one of the most frequently used indicators of quality. However, its theoretical relation with efficiency is ambiguous. Thus, an inverse relationship can arise if a higher mortality rate necessitates the provision of intensive care (e.g., due to a more complex case-mix), whereas a direct relation will be observed if a high mortality rate represents lower levels of care due to a mismanagement [20]. We used a measure of risk-adjusted mortality estimated as the ratio of observed to expected mortality rate during isolated coronary angiography [44]. Higher levels of risk-adjusted mortality represent worse department quality.

Finally, patient radiation exposure is an indicator of the process quality. It has been argued that process indicators should not be included into the efficiency analysis because it is not an output of production process [45]; however, several previous studies included process indicators either to augment the production set [6,11,46] or to explore the relationship with the distribution of inefficiencies in the two-stage analysis [22,23,25]. To shed new light on this discussion we explored whether and how a process indicator enters the production process. In our study, radiation exposure was measured as the proportion of patients exposed during coronary angiography to a radiation dose over 3.500 cGy*cm^2 [44]. Again, higher values of patient radiation exposure represent worse quality.

Results

Descriptive statistics

Table 1 provides summary statistics for the utilized sample. In total, 178 cardiology departments provided complete data on the clinical measures of quality and at least 30 surveys of patient satisfaction. Thus, our sample represents approximately 25% of interventional cardiology departments in Germany. On average, a cardiology department in our sample employed 25 full-time physicians and 86 full-time nurses to produce 3,950 inpatient discharges adjusted for case-mix.

Table 1: Descriptive statistics

	N	Mean	SD	Min	Max
INPUTS					
Physicians [FTE]	178	25	17	6	125
Nurses [FTE]	178	86	124	9	865
OUTPUTS					
Inpatient discharges	178	3,950	1,568	874	13,076
QUALITY					
Patient satisfaction	178	2.01	0.31	1.30	3.16
Risk-adjusted mortality	178	1.10	0.76	0.00	3.94
Patient radiation exposure	176	0.27	0.15	0.01	0.64

Notes: Data for calendar year 2012. FTE = full time equivalents, N = number of departments, SD = standard deviation.

Considering the quality measures, the mean patient satisfaction equaled 2.01, which indicates that most patients were rather satisfied with their stay at the cardiology departments (because 1 is the highest possible value and 6 is the lowest possible value of satisfaction). The department average value of satisfaction varied between 1.30 and 3.16. The mean value of risk-adjusted mortality equaled 1.10 (range: 0 to 3.94), meaning that, on average, the observed values of mortality only slightly exceeded the predicted values of mortality. Finally, the mean value of patient radiation exposure was 0.27 (range: 0.01 to 0.64), indicating that, on average, less than a third of patients was exposed to a dangerously high radiation dose during coronary angiography.

Efficiency estimates

We applied the aggregation procedure to reduce the number of input dimensions using the methodology described in Daraio & Simar [47]. The benefits of working in smaller dimensions include, first, better rates of convergence and thereby a more precise estimation of the frontier and, second, the opportunity to examine the results graphically. The two mean-standardized labor inputs were aggregated using principal component analysis to obtain the one-dimensional input factor: $X = 0.71\, physicians + 0.71\, nurses$. The resulting input factor is highly correlated with the original inputs; therefore, we do not lose much information.

Table 2 summarizes the obtained efficiency estimates. In the output-oriented framework, efficiency estimates equal to 1 represent efficient observations and efficiency estimates greater than 1 represent inefficient observations. Because we rely on the partial frontier analysis of order-m ($m = 80$), some efficiency estimates are smaller than 1. These estimates represent observations that are more efficient than the average 80 benchmark observations. The mean value of unconditional efficiency estimates (i.e., not considering quality differences) equals 1.41. This means that expanding the output could lead to the reduction of inefficiency by 41%.

Table 2: Efficiency estimates

	N	Mean	SD	Min	Max
Unconditional efficiency estimates $\hat{\lambda}(x, y)$					
	178	1.41	0.46	0.78	4.29
Conditional efficiency estimates $\hat{\lambda}(x, y \vert z)$*, where…*					
$z = Z_1$ (patient satisfaction)	178	1.40	0.44	0.85	4.27
$z = Z_2$ (risk-adjusted mortality)	178	1.33	0.41	0.90	4.30
$z = Z_3$ (patient radiation exposure)	176	1.38	0.47	0.82	4.27

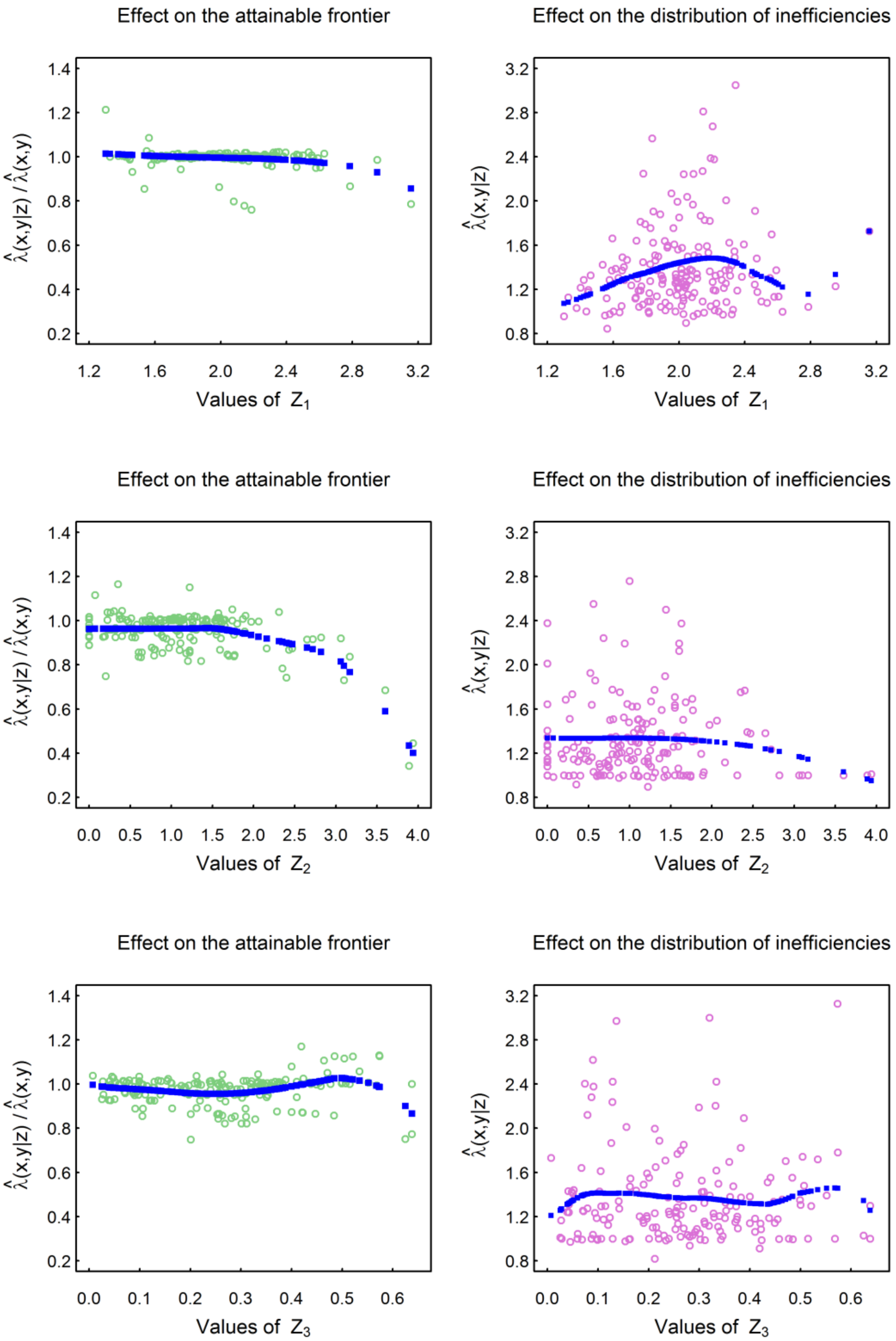
Notes: Higher values of efficiency estimates represent higher inefficiency. N = number of departments, SD = standard deviation

Next, we condition the efficiency analysis on quality and obtain the mean values of conditional efficiency estimates equal to 1.40, 1.33, and 1.38 for patient satisfaction, risk-adjusted mortality, and patient radiation exposure respectively. The mean values of conditional efficiency estimates are smaller than the mean value of unconditional efficiency estimates, because we compare units at the similar levels of quality. However, only in case of risk-adjusted mortality, the difference in the mean values is substantial, which provides some indicative evidence that only risk-adjusted mortality has an effect on the shift in the attainable frontier.

Effect of quality on the production process

Using nonparametric regression analysis, we investigate the mechanisms how the measures of quality affect the production process. The left panel of Fig. 2 provides the results of the nonparametric regression of the ratios of conditional to unconditional efficiency estimates $\hat{R}(x,y|z) = \hat{\lambda}(x,y|z)/\hat{\lambda}(x,y)$ on Z. These results are informative about the potential shift of the attainable frontier due to Z. The right panel of Fig. 2 illustrates the results of the regression of conditional efficiency estimates $\hat{\lambda}(x,y|z)$ as a function of Z that are indicative of the effect of Z on the distribution of the inefficiencies within the production set.

Figure 2:



Legend Figure 2: The relationship of quality measures with the production process. Scatterplot of the ratios $R = \lambda(x, y|z)/\lambda(x, y)$ against Z (left panel); scatterplot of the conditional efficiencies $\lambda(x, y|z)$ against Z (right panel). The mean values of the corresponding nonparametric regressions are depicted with dark blue squares. Z_1 = patient satisfaction, Z_2 = risk-adjusted mortality, Z_3 = patient radiation exposure.

In case of patient satisfaction (Z_1), the results suggest that there is no effect of Z_1 on the attainable frontier because the mean values of the nonparametric regression of $\hat{R}(x, y|z)$ on Z_1 form a flat line (the left panel). In contrast, there is a visible inverted U-shaped effect of Z_1 on the distribution of inefficiencies (the right panel). Near the center, the distribution of the inefficiencies is largest; however, at both high and low patient satisfaction, the departments are more efficient, i.e., characterized by low values of inefficiency.

In case of risk-adjusted mortality (Z_2), the results of the nonparametric regression of $\hat{R}(x, y|z)$ on Z_2 show that there is a shift of in the attainable set associated with Z_2 (the left panel). Because we are using the output-oriented model, a decreasing regression line indicates that the production process is adversely affected by risk-adjusted mortality. The results of the nonparametric regression of the $\hat{\lambda}(x, y|z)$ on Z_2 show that risk-adjusted mortality does not affect the distribution of inefficiencies, because the average regression values form almost a flat line (the right panel).

Patient radiation exposure (Z_3) seems not to have an effect on efficiency. There is almost no observable effect of patient radiation exposure either on the shift in the boundary of the attainable set or on the distribution of inefficiencies. The lines formed by the mean regression values are roughly flat in both regressions.

Discussion

In this study, we applied the conditional approach to analyze the relationship between technical efficiency and three different measures of quality, including patient experience and outcome and process quality indicators. We used data on 178 departments of interventional cardiology, which ensured a good comparability of the analyzed units. Two different nonparametric regressions were used to investigate the channel through which quality affected the production process. The regression of the ratios of conditional to unconditional efficiency estimates on quality provided evidence about the effect of quality on the attainable frontier, whereas the regression of the conditional efficiency estimates on quality revealed the effect of quality on the distribution of inefficiencies. Our results refute the existence of a trade-off between efficiency and quality. In our study, the relationship between efficiency and quality seems much more complex and turns out to be highly dependent on the type of the utilized measure of quality.

The measure of patient satisfaction does not have an effect on the attainable frontier; however, there is an inverted U-shaped effect of the patient satisfaction on the distribution of the inefficiencies. Cardiology departments with both the highest and lowest values of patient satisfaction are relatively efficient, whereas departments with median values of patient satisfaction are characterized by the highest dispersion in the inefficiencies and are also, on average, the least efficient. The fact that some providers manage to achieve both high values of efficiency and patient satisfaction indicates that high efficiency may be achieved without a significant sacrifice of service quality, which corresponds to the philosophy of total quality management (TQM) [16]. However, the departments that maintain high efficiency at low values of patient satisfaction may indeed sacrifice the humanity of care to gain productivity [31].

The effect of the risk-adjusted mortality on the production process is quite different. Risk-adjusted mortality has an unfavorable effect on the attainable frontier whereas the effect on the distribution of inefficiencies is rather small. The effect on the attainable frontier is more pronounced at high than at low values of risk-adjusted mortality. In fact, there is a negative effect on the shift of the attainable frontier for cardiology departments, in which the observed mortality more than doubles the predicted mortality. Therefore, cardiology departments with high mortality rates require more input resources per patient. This finding is consistent with of Clement et al. [13] who discovered that technical inefficiency was associated with higher risk-adjusted mortality rates.

The measure of patient radiation exposure represents process quality and it does not seem to have an effect on the production process. This quality measure does not have an effect either on the attainable frontier or on the distribution of the inefficiencies. This result is important because it highlights the difference between process and outcome indicators. It lends some support to a proposition that process measures should not be directly included in efficiency models [45].

Limitations

Our empirical analysis has some limitations. First, the analysis is based on cardiology departments and may not be generalizable to other medical specialties. However, we believe that the focus on one medical specialty enables a better selection of comparable units for the efficiency analysis than a focus on the entire hospital, because departments of the same medical specialty have similar structures, use similar technology, and produce more homogenous outputs [48]. Second, our input measure contains only labor but not capital resources, which are usually represented by the number of beds. However, this information is not reported at the department level in Germany. Nevertheless, we believe that capital intensity is similar across departments, because hospitals are required by law to maintain certain number of beds and technology equipment. In addition, we concentrate on a homogenous subset of cardiology departments that perform interventional procedures. Moreover, we did not account for hospital characteristics, such as ownership type or university status, to avoid increasing the dimensions of the production process with only 178 observations. However, some of the unexplained differences in efficiency may be related to the institutional characteristics of the analyzed departments.

Additionally, the empirical analysis is complicated by little variation in the patient satisfaction measure because of high satisfaction rates of patients [49] and a response bias, because dying patients and patients with severe post-acute complications are less likely to take part in a survey. However, both efficient and inefficient departments are similarly affected by these potential biases and, therefore, conclusions can still be drawn from our results. On the other hand, many of the nationally selected measures of inpatient clinical quality are contested for their imprecise documentation and risk adjustment. To account for this critique, we selected two quality indicators that were both adjusted for case-mix and rated by experts as having good theoretical and empirical explanatory power [50].

Methodological and policy implications

This study applies the nonparametric conditional approach to investigate the role of quality in the efficiency performance of hospital cardiology departments. The advantage of our approach is that quality is introduced in a non-restrictive way. Given the empirical findings of our study, different measures of quality can have an effect either on the attainable frontier or the distribution of the inefficiencies, and the effect may be nonlinear. Therefore, a model that allows the differential effect of quality on the production process is the most appropriate to integrate quality into the analysis of health care efficiency.

In contrast, the traditional methods to incorporate quality in the analysis of efficiency require making quite restrictive assumptions. Thus, the one-stage approach, which treats quality as another output variable in the DEA analysis under the assumption of strong disposability, requires that quality has a negative effect on the attainable frontier, which may or may not be supported by the data. In fact, in our dataset, only the measure of risk-adjusted mortality has an effect on the attainable frontier. If we would transform this measure to obtain the inverse of the risk-adjusted mortality (to represent the concept that more is better), then the effect of quality on the attainable frontier would be positive. Therefore, it would be incorrect to add this measure as another output variable. The congestion analysis, which adds the measures of the lack of quality to outputs under the assumption of weak disposability, could be applied in our dataset to the measure of risk-adjusted mortality. However, the congestion analysis would fail to identify the inverted U-shaped relationship between patient satisfaction and the distribution of the inefficiencies. Moreover, both the one-stage approach and the congestion analysis impose other restrictive assumptions on the dataset augmented by the measures of quality, such as monotonicity, convexity, and returns to scale. It is conceivable that not all these assumptions will be supported by empirical datasets.

The two-stage approach estimates the efficiency scores without considering quality in the first stage and regresses the obtained estimates on the measures of quality in the second stage. Thus, there is no need to impose additional assumptions on the quality measures in the first stage. However, in situations when quality does have an effect on the shift of the attainable frontier, the estimates obtained in the first stage are biased because they compare decision-making units with different attainable frontier levels against a common benchmark. In our empirical example, risk-adjusted mortality has an effect on the shift the attainable frontier, in which case the separability condition between the attainable set and the measure of quality is not verified. Simar & Wilson [29] do not recommend using the two-stage approach in such situations. Nevertheless, the other two quality indicators in our empirical analysis do not have an effect on the shift of the attainable frontier and could be examined by the two-stage approach.

Therefore, the distinction of the channels through which quality enters the production process is crucial to the selection of the methodology to examine the trade-off between efficiency and quality. A misapplication of the traditionally used methods can potentially lead to incorrect managerial and policy implications. The inference about the relationship between efficiency and quality is only possible when the analyst has a clear understanding of the underlying assumptions. Future research would benefit from the insights regarding the theoretical foundation that underlies the mechanisms through which quality impacts the production process of health care institutions. This would necessitate exploring different types of quality measures in conjunction with different health care institutions. Another useful research extension would be to analyze the role of institutional and environmental characteristics in the relationship between efficiency and quality.

Conclusion

Contemporary health care policy is concerned with increasing the efficiency of the hospital sector while improving the quality of provided care. Policy makers in different countries are interested in reforming reimbursement systems to reward superior quality through various pay-for-performance programs [1]. Therefore, understanding the potential trade-off between efficiency and quality is paramount for decision makers to allocate constrained resources between and within hospitals. The literature, however, provides scant and ambiguous empirical evidence on this trade-off, which is to some extent due to the use of methods that are based on different assumptions about the role of quality in the production process. Therefore, we add to the literature by shedding light on the channels through which different measures of quality impact the efficiency of health care providers.

This is the first study to apply the conditional approach to integrate quality into the analysis of efficiency using health care data. The conditional approach allows benchmarking units at similar levels of quality and enables differentiating between the effect of quality on the shift of the attainable frontier and on the distribution of inefficiencies. In our empirical analysis of the data from 178 cardiology departments, each quality measure deserves an individual examination, because the relationship between efficiency and quality varies according to the type of measure. Thus, patient satisfaction does not have an effect on the attainable frontier, but it affects the distribution of the inefficiencies within the production set. Cardiology departments with the highest and the lowest values of patient satisfaction achieve the best efficiency, whereas departments with the median values of patient satisfaction achieve rather low values of efficiency. The measure of risk-adjusted mortality has a negative effect on the attainable frontier, suggesting that departments with the highest mortality rates are characterized by the highest resource intensity. Therefore, instead of a trade-off between efficiency and quality, we observe a positive association between efficiency and quality in case of risk-adjusted mortality. Finally, the measure of patient radiation exposure, which represents the process dimension of quality, has neither an effect on the attainable frontier nor an effect on the distribution of inefficiencies. Our results confirm that, because different measures of quality may have differential effects on the production process, policy makers and researchers should be careful when selecting the methods and interpreting the influence of single quality indicators on efficiency.

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