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## Who is an efficient and effective physician?

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**Evaluating physicians' performance is of great interest to public policy makers, researchers, and hospital managers. Despite recent advances, however, a fair and scientific method of evaluating physicians' performance has yet to be seen. In this study, we use Data Envelopment Analysis (DEA) to analyze, and propose two metrics for evaluating physicians' performance in terms of effectiveness and efficiency. We apply our analysis to a large data set of care delivered by Emergency Department (ED) physicians. We then carry out a Tobit analysis to identify factors that are associated with higher levels of physician performance. In addition to factors related to patient and physician characteristics, our findings provide strong evidence for the effect of peer characteristics and suggest that peer diversity could improve a physician's performance.**

### **Introduction**

According to a recent report by the Centers for Medicare and Medicaid Services, healthcare spending is projected to rise to 19.9% of the GDP by 2025 (1). The rising costs of healthcare

have drawn much attention to finding new ways to reduce costs by increasing both the efficiency and effectiveness of care delivery. Given that decisions on utilization of healthcare services are ultimately made by frontline clinicians (2), evaluating physicians' efficiency and effectiveness in a fair and scientific manner could not only significantly help to identify the sources of waste in healthcare spending, but also contribute to guidelines with respect to adding correct incentives to healthcare reimbursement.

Although an increasing number of care delivery performance measurement initiatives have been undertaken in recent years, the healthcare sector has yet to develop rigorous scientific methods of evaluating the efficiency and effectiveness of physicians. In this study, we use Data Envelopment Analysis (DEA)—a linear programming (LP) optimization technique that provides a multi-dimensional evaluation tool—to evaluate two candidate metrics for evaluating physicians' effectiveness and efficiency. We apply our proposed models and metrics to a large dataset of care delivered by Emergency Department (ED) physicians that includes more than 115,000 visits. In order to identify characteristics of effective and efficient physicians, we use the scores derived from our DEA models to conduct a second-stage analysis in which we use a Tobit framework to identify factors (e.g., MRI count, Lab test count, physician-patient contact time, etc.) that are associated with higher levels of physician performance. We also use our framework to study peer effect: the effect of the characteristics of another physician who is scheduled to work side-by-side with the first physician. We consider peer physician characteristics such as relative effectiveness, efficiency, experience, sex, and medical degree (MD vs. DO), and examine how they affect another physician's effectiveness and efficiency. In order to obtain a relative assessment of physicians' effectiveness and efficiency, we also make use of clustering techniques including k-means, spectral, and random forest algorithms to segment physicians based on their effectiveness and efficiency scores.

Our results offer potential insights into physicians' efficiency and effectiveness. Contrary

to the conventional wisdom that effectiveness comes at the price of efficiency, our findings demonstrate a statistically significant positive association between a physician's effectiveness and efficiency ( $P = 0.044$ ). We also find that a physician's efficiency is negatively associated with his/her contact time with patients ( $P < 0.0001$ ) and positively associated with his/her admission rate ( $P < 0.0001$ ). In addition, we observe a statistically significant negative relationship between a physician's effectiveness and his/her average number of lab orders ( $P < 0.0001$ ), caseload ( $P = 0.045$ ), and admission rate ( $P < 0.0001$ ).

Our findings with regards to physician peer effects (which can have important implications for physician scheduling) suggest a statistically significant impact of peer effect on each physician's performance. Our findings suggest that peers with diverse characteristics in terms of relative efficiency, effectiveness, and experience improve a physician's performance. Specifically, we observe that an average physician's efficiency score is improved when he/she is scheduled to work with a more effective peer ( $P = 0.0002$ ). Similarly, our results show a statistically significant positive association between a physician's effectiveness score and the presence of a less experienced peer ( $P = 0.012$ ). In addition, we observe a negative association between a physician's effectiveness score and the presence of a more effective peer ( $P < 0.0001$ ).

## **Data**

The data consist of detailed care delivery information in a leading U.S. hospital associated with 32 ED physicians. The patients are randomly assigned to physicians upon arrival through an algorithmic rotational patient assignment process (3). This workflow essentially removes all patient selection biases or preferences of physicians in selecting their patients, providing us with a unique opportunity to treat performance outcomes in this setting as almost entirely natural experiments. We included all patients who presented from July 12, 2012, to July 31, 2016 and were seen by an ED physician in our analysis. Patient specific-data included demographic (age,

sex, race, etc.) and insurance information. Encounter-level data included labs, chief complaint, Emergency Severity Index (ESI), day of the ED visit, time of day, etc., totaling over 70 variables. A complete list of these variables is available as a supplementary material. To avoid distortion of the results by outliers, 6 physicians with relatively low patient volumes (fewer than 250 visits over the 4 year period) were excluded from the analysis.

## DEA Models

DEA, first introduced by Charnes, Cooper, and Rhodes in (4), is a methodology useful in evaluating the relative performance of a set of decision making units (DMUs) in a multiple input, multiple output setting. The conventional input-oriented DEA methodology evaluates each DMU  $j$  in the population based upon a set of inputs  $\{x_{ij}\}_{i=1}^I$  and outputs  $\{y_{rj}\}_{r=1}^R$  while assuming a proportional reduction in all inputs. In an output-oriented setting, this methodology will provide for a proportional expansion in outputs rather than a reduction in inputs. For the goals of this study, we have chosen the input-oriented mechanism.

The original DEA model was based on a constant returns to scale (CRS) methodology. Banker, Charnes, and Cooper (5) extended the CRS model to allow for variable returns to scale (VRS). The input-oriented CRS model is based on the Linear Program (LP):

$$\begin{aligned}
 \text{max} \quad & \theta = \frac{\sum_r u_r y_{rj_o}}{\sum_i v_i x_{ij_o}} & (1) \\
 \text{s.t.} \quad & \frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1 & j = 1, \dots, n, \\
 & u_r, v_i \geq 0, & r = 1, \dots, R; \quad i = 1, \dots, I,
 \end{aligned}$$

where  $y_{rj_o}$  and  $x_{ij_o}$  represent the output(s) and input(s) of DMU  $j_o$ , respectively, and  $\{u_r\}_{r=1}^R$  and  $\{v_i\}_{i=1}^I$  are decision variables.

In order to develop scientific scores to evaluate the performance of physicians in terms of

their effectiveness and efficiency, we develop two DEA models: an effectiveness DEA model that scores physicians based on the percentage of patients who do not return to the ED within 72 hours, and an efficiency DEA model that scores physicians based on their patients' length of stay. In both models, DMUs comprise individual physicians who use hospital resources to deliver care. The choice of the input and output variables in each model is based on the view of the physician as a production entity which utilizes a number of hospital resources (inputs) to generate effective and efficient care (outputs). It is important to note that there is no objective definition of the right variables to use as inputs and outputs. We have chosen herein to define the models' input and output variables in terms of parameters that (a) best reflect a physician's performance, and (b) for which there is at least face validity among physicians. As robustness checks, we have repeated our analyses with different combinations of input/output variables, and have observed that the majority of our main results presented in the "Discussion and Results" section hold. In addition, we used Wagner and Shimshak's (6) stepwise variable selection algorithm to validate our choice of model variables. The results of applying this algorithm to both the effectiveness and efficiency models are available as supplementary materials. It should be noted that the choice of our models' input/output variables is largely data-dependent. While the analysis provided herein is based on quantitative data, it is reasonable to argue that inclusion of qualitative factors could improve the strength and applicability of both models. The models' variables include:

### **Effectiveness DEA Model**

Output:

- *72-Hour Non-Return Patient Visits*: Since a high 72-hour return rate can be considered an undesirable indicator of care delivery effectiveness, we use the proportion of patients treated by a physician who were not admitted to the hospital within 72 hours of their

original discharge as the physician's output variable.

Inputs:

- *Ultrasound Order Count*: Average number of the physician's ultrasound orders per patient visit
- *IV Med/Fluid Count*: Average number of the physician's IV Med/Fluid orders per patient visit
- *Radiology Order Count*: Average number of the physician's radiology orders per patient visit.

We considered but excluded other resource utilization inputs. The MRI order count was not included in the model because of its negative correlation with the output variable. The CT scan order count was omitted from the analysis because of its strong correlation with the other input variables. We refer to  $\theta$  scores (see Eq. (1)) generated by the DEA model with the above input-output parameters as the physicians' effectiveness scores.

### **Efficiency DEA Model**

Output

- *Inverse LOS*: Inverse of a physician's average patient Length of Stay (LOS)

Inputs:

- *Lab Order Count*: Average number of the physician's lab orders per patient visit subtracted from the highest average number of lab orders of all physicians
- *CT Scan Order Count*: Average number of the physician's CT scan orders per patient visit subtracted from the highest average number of CT scan orders of all physicians

- *MRI Order Count*: Average number of the physician's MRI orders per patient visit subtracted from the highest average number of MRI orders of all physicians
- *Ultrasound Order Count*: Average number of the physician's ultrasound orders per patient visit subtracted from the highest average number of ultrasound orders of all physicians
- *IV Med/Fluid Count*: Average number of the physician's IV med/fluid orders per patient visit subtracted from the highest average number of IV med/fluid orders of all physicians
- *Radiology Order Count*: Average number of the physician's radiology orders per patient visit subtracted from the highest average number of radiology orders of all physicians

We refer to  $\theta$  scores (see Eq. (1)) generated by the DEA model with the above input-output parameters as the physicians' efficiency scores. Since a high average LOS is an undesirable output, the inverse of this measure is used in the analysis. Because of the negative relationship between a physician's test order counts (inputs) and LOS (output), all test order counts are considered undesirable inputs with respect to the output. Hence, to represent the time saved when a physician does not order a test, a physician's average number of test orders subtracted from the highest average number of tests ordered by any physician (worst-case scenario) is considered as an input. We tested the robustness of this assumption by also considering 1.25, 1.5, 1.75, and 2 times the highest average number of test orders of all physicians as the worst-case scenario.

### **Peer-Effect DEA Model**

In order to examine the effects of peer presence on a physician's effectiveness and efficiency, we use a variation of the proposed DEA models in which each DMU, denoted by  $J_k$ , comprise a physician  $j$  who has worked alongside his/her peer physician  $k$  for at least 5 hours. We choose the 5-hour criterion to be able to capture any peer physician effect. To confirm that our results

were not sensitive to the choice of the 5-hour shift, we repeated our analysis for 3 and 8-hour shifts and observed no significant difference in outcomes. Thus, we utilize a total of four DEA models (effectiveness and efficiency both for individual and peer effect performance).

All these four models were tested for isotonicity. A regression and correlation analysis confirmed that a positive association existed between the inputs and the outputs ( $P = 0.001$ ) and a moderate intercorrelation between the input variables ( $P = 0.008$ ).

Since there is no reason to believe that an increase in inputs results in a proportional change in the outputs, a variable returns to scale model was used. This assumption was tested by Simar and Wilson's (7, 8) returns-to-scale tests for input-oriented DEA models. We further assume that the quantity of inputs are treated as endogenous and hence are influenced by physicians. For this reason, an input-oriented approach was used to test whether a DMU under evaluation can reduce its inputs while keeping the outputs at their current levels.

## **Physician Classification**

Prior to examining the drivers of physician performance, we developed a classification scheme that allowed for a relative comparison of physician performance based on their generated effectiveness and efficiency scores (see Fig. 1).

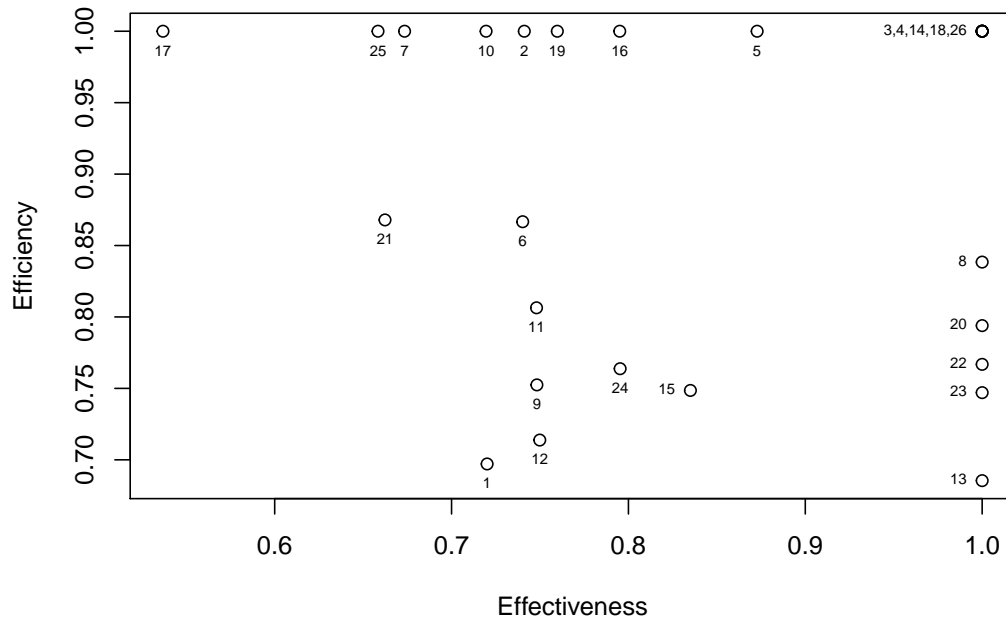


Fig. 1: Physicians' Performance Scores

A number of classification algorithms including k-means, spectral, and random forest were used to categorize physicians into the following four groups based on their scores:

*Group 1.* Highly effective / Highly efficient

*Group 2.* Highly efficient / Lowly effective

*Group 3.* Highly effective / Lowly efficient

*Group 4.* Lowly efficient/ Lowly effective

Fig. 2 demonstrates how physicians are partitioned into the aforementioned clusters using the k-means algorithm which creates groups based on the euclidean distance between the data points.

Fig. 3 presents the clustering of physicians based on the random forest algorithm, and Fig. 4 illustrates the results based on the spectral clustering algorithm.

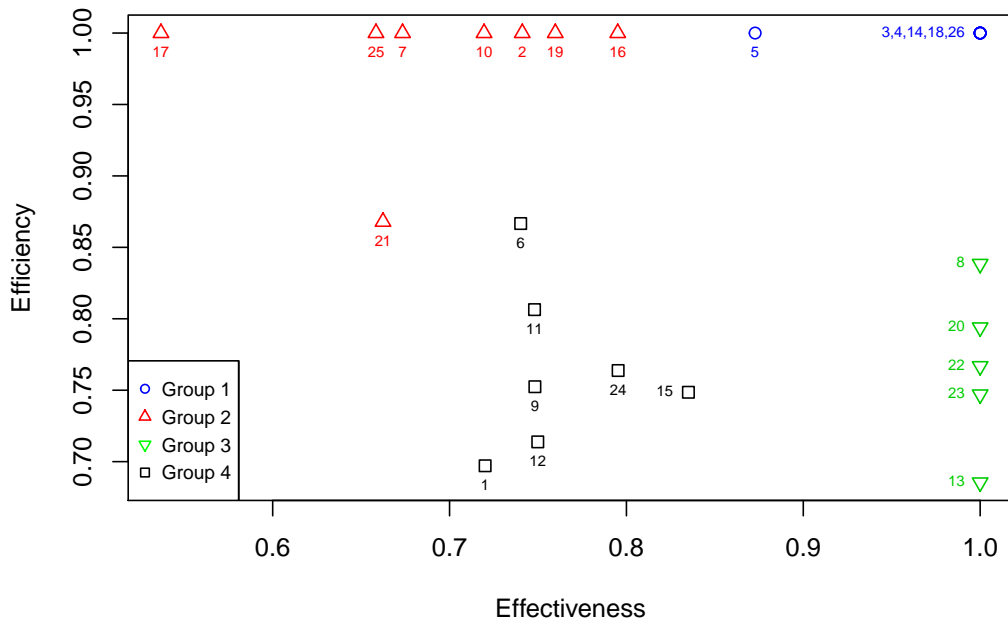


Fig. 2: K-means Clustering - Silhouette coefficient = 0.7239

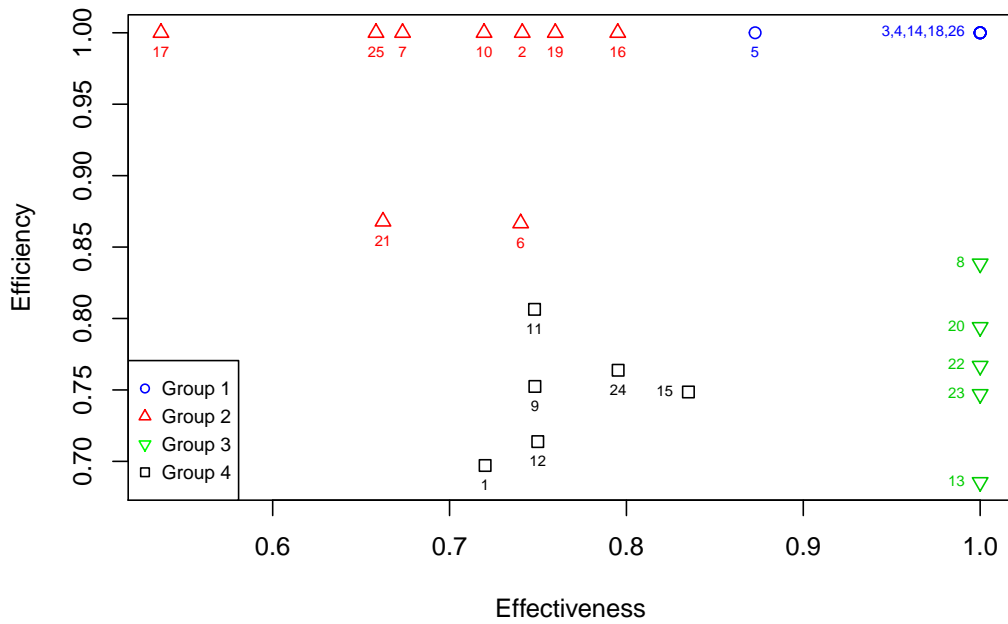


Fig. 3: Random Forest Clustering - Silhouette coefficient = 0.6990

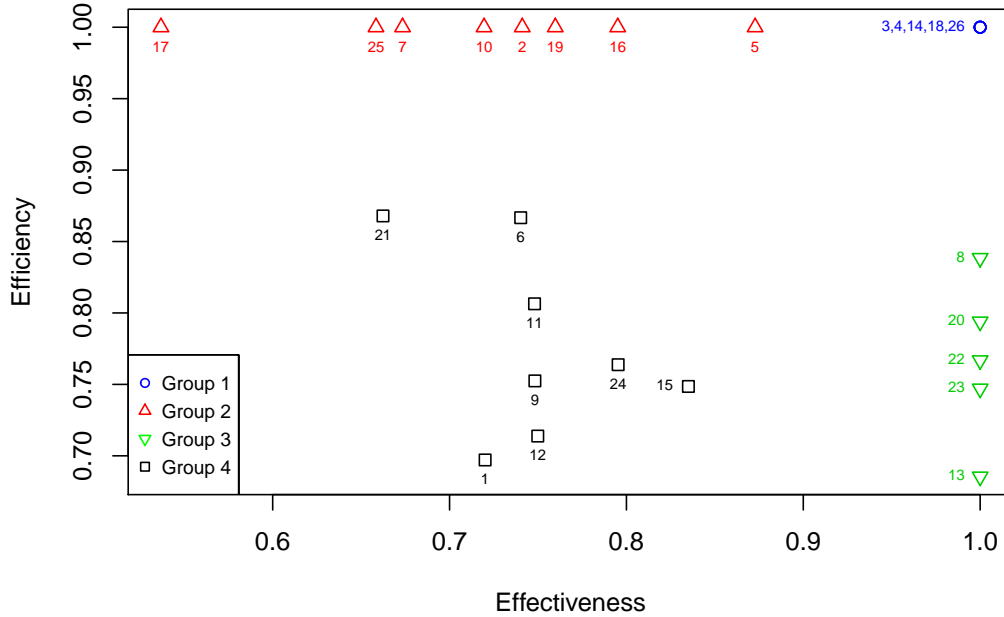


Fig. 4: Spectral Clustering - Silhouette coefficient = 0.1045

We compared the performance of all three algorithms using the Silhouette clustering evaluation criterion (9) which provides an index measuring both cluster cohesion and separation, and concluded that the k-means algorithm provides the most accurate classification of physicians. Thus, we assign each physician to one of the four groups based on the classification provided by the k-means algorithm (Fig. 2).

## Statistical Methodology

In order to examine factors affecting physician performance, we regress the generated DEA scores of physician  $i$  ( $\theta_i$ ), on a set of explanatory variables related to patient, physician, and peer physician  $j$  characteristics which we denote by  $U_i$ ,  $W_i$ , and  $Z_{ij}$ , respectively. The regression model takes the following general form

$$\theta_i = a + U_i\gamma + W_i\alpha + Z_{ij}\beta + \epsilon_i, \quad (2)$$

where  $\epsilon_i$  is a statistical noise and  $a$  is a fixed effect (constant).

In order to estimate the coefficients in equation (2), a regression technique other than the standard multivariate regression is needed. This is because this standard regression technique assumes a normal and homoscedastic distribution of the noise. However, since the DEA scores are between 0 and 1, our dependent variable is bounded and error terms may not satisfy these assumptions.

Tobit regression can be used whenever there is truncation, causing a mass of observations at a threshold value such as 0 or 1. But unlike the case of truncation, DEA does not exclude observations greater than 1 (or below 0), rather the analysis does not allow a DMU to be assigned a value outside the range [0, 1]. Hence, DEA easily fits the requirement of the Tobit model (10).

Following the normalization approach of Greene (10, 11) which assumes a censoring point at zero, we transform the DEA scores to:

$$y_i = (1/\theta_i) - 1$$

where  $\theta_i$  is the DEA measure of physician  $i$  performance. Once the DEA scores have been transformed, the slope coefficients of Tobit represent the change in the dependent variable for a one unit change in the independent variable, holding all else constant. Thus, the transformed DEA scores become the dependent variable that takes the form:

$$y_i = \begin{cases} B'x_i + u_i, & \text{if } y_i > 0, \\ 0, & \text{otherwise,} \end{cases}$$

where  $B$  is a  $k \times 1$  vector of coefficients and  $x_i$  is a  $k \times 1$  vector of covariates, and  $u_i$  is the error term that is normally distributed with a mean of zero and a variance of  $\sigma^2$ . To account for unobserved serial correlation in the DEA scores, we used Simar and Wilson's bootstrap procedure (12) for bias-correction of the scores.

## Discussion and Results

We begin our analysis by examining the relationship between physicians' effectiveness and efficiency scores. Importantly, we find that higher levels of treatment effectiveness do not lead to lower efficiency, as the conventional wisdom would suggest. Rather, there is a statistically significant positive relationship between the two scores (presented in Table 1). This is an important observation, especially in the view of traditional debates that argue healthcare providers cannot become both more effective and more efficient.

Table 2 presents our regression results for individual physician effectiveness scores. We find a statistically significant positive association between a physician's effectiveness and his/her patients' average ESI level. This is rather expected because patients with higher ESI levels are less severe patients and treating them in an effective way is typically easier.

From Table 2, we also observe a statistically significant negative correlation between a physician's effectiveness score and his/her admission rate, indicating that more effective physicians have lower admission rates on average. This finding is somewhat paradoxical, in that a reasonable initial assumption is that physicians with lower admission rates are sending home more borderline cases than their peers with higher admission rates, and that these borderline discharges would be more likely to return to the hospital.

The regression results regarding the peer physician effectiveness analysis (presented in Table 3), indicate a statistically significant negative relationship between a physician's effectiveness and his/her average number of lab orders. Hence, we conclude that more lab tests make a physician less effective. This is consistent with previous findings in the literature that suggest a higher number of diagnostic tests ordered by physicians does not necessarily lead to a better care (13). Our finding, however, is also somewhat paradoxical, in that a reasonable initial assumption

is that physicians who order more tests define their patients more completely, which should make these patients less likely to return within 72 hours. The fact that physicians with lower admission rates and lower resource utilization profiles have higher effectiveness scores support a theory that there are inherent differences between physicians with respect to effectiveness.

Table 3 also indicates a negative relationship between a physician's effectiveness and his/her case load (patients per hour). This supports the conventional wisdom that overwhelmed physicians might be less effective (i.e. a Yerkes-Dodson effect), although we note that this relationship might not be causal.

The regression results regarding individual physician efficiency are displayed in Table 4. The results indicate a statistically significant negative relationship between a physician's efficiency score and his/her experience level. This is a rather surprising result, which questions the traditional belief that years of experience enable physicians to use hospital resources more appropriately. This might be due to the recent changes in medical training that require trainees to think more about efficient use of healthcare resources, though our data is insufficient in this regard. The peer physician efficiency results (presented in Table 5) indicate a positive relationship between a physician's efficiency score and his/her admission rate, and a negative association between efficiency and the physician's contact time with the patient.

With regards to peer effects, our results (presented in Table 6) show a statistically significant negative relationship between a physician's effectiveness and the presence of a more effective peer. In addition, our results demonstrate a positive association between effectiveness and working alongside a less experienced peer. These suggest that, all else equal, boosting a physician's effectiveness requires scheduling him/her with a less effective physician or with a less experienced physician.

The regression results of peer physician efficiency analysis (displayed in Table 7) show that the presence of a more efficient peer is associated with a decrease in physician efficiency on

average. Conversely, working alongside a more effective peer has a positive association with physician efficiency.

## Conclusions

In this paper, we propose two scientific metrics for evaluating physicians' performance in terms of effectiveness and efficiency. We use our proposed metrics to examine factors associated with physicians' performance. We find that a physician's resource utilization behavior in terms of hospital admissions and diagnostic tests is associated with his/her effectiveness and efficiency. In addition, our results present strong evidence for the existence of peer effects and suggest that the presence of diverse peers has a positive effect on a physician's effectiveness and efficiency. Our findings are valuable not only in terms of finding new ways to improve the efficiency and effectiveness of healthcare delivery, but also in research areas such as physician scheduling where one needs to decide which providers should be scheduled during the same shift. Moreover, this study highlights the need for further theoretical research on the drivers of physicians' performance. Future work would provide a more complete picture of the channels through which a physician's effectiveness and efficiency may be positively affected.

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## **Supplementary Materials**

Materials and Methods

Table S1 - S2

Table 1: Regression Results - Effectiveness vs. Efficiency

<i>Dependent variable: DEA Effectiveness Score</i>	
DEA Efficiency Score	0.5832* (0.2902)
<i>Patient Characteristics</i>	
Avg Patient ESI Level	-3.5547* (1.6607)
Patients Over 65 Years of Age (%)	-3.6065 (2.3696)
Female Patients (%)	-1.8786 (2.7210)
White Patients (%)	3.9159 (3.7802)
<i>Physician Characteristics</i>	
Physician Experience	0.0033 (0.0033)
Physician Case Load	-0.0352 (0.0311)
Physician-patient Contact Time	-0.0016 (0.0010)
Physician Admit Rate	-3.3398*** (0.6621)
Avg Total ED Patients per Shift	0.0198* (0.0082)
Constant	-2.5120*** (0.1443)

*Note:* p<0.1; \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 2: Regression Results - Effectiveness Model - Individual Physician

<i>Dependent variable: DEA Effectiveness Score</i>	
<i>Patient Characteristics</i>	
Avg Patient ESI Level	2.0944* (0.9826)
Patients Over 65 Years of Age (%)	-0.4905 (1.4444)
Female Patients (%)	0.3448 (1.8183)
Avg MRI Count	-0.8227 (2.1809)
Avg Lab Count	-0.0065 (0.0132)
White Patients (%)	-3.6642 (2.9262)
<i>Physician Characteristics</i>	
Physician Experience	-0.0018 (0.0021)
Physician Case Load	-0.0096 (0.0222)
Physician-patient Contact Time	-0.0003 (0.0008)
Physician Admit Rate	-1.3694* (0.5700)
Constant	-2.6563*** (0.1387)

*Note:* p<0.1; \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 3: Regression Results - Effectiveness Model - Peer Physician

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*Dependent variable: DEA Effectiveness Score*

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<i>Patient Characteristics</i>	
Avg ESI Level	0.2798*** (0.0721)
Over 65 Years of Age (%)	-0.1473 (0.1001)
Females (%)	0.0309 (0.0997)
Whites (%)	-0.3904 (0.1858)
<i>Physician Characteristics</i>	
Avg MRI Count per Patient Visit	0.4680* (0.2353)
Avg Lab Count per Patient Visit	-0.0254*** (0.0037)
Physician Case Load	-0.0489 * (0.0244)
Physician-patient Contact Time	-0.0009*** (0.0003)
Physician Admit Rate	-0.4012*** (0.1003)

Table 4: Regression Results - Efficiency Model - Individual Physician

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*Dependent variable: DEA Efficiency Score*

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<i>Patient Characteristics</i>	
Avg Patient ESI Level	1.1018 (0.6513)
Patients Over 65 Years of Age (%)	0.9580 (1.0048)
Female Patients (%)	-1.1854 (1.4283)
White Patients (%)	-1.5198 (2.2686)
<i>Physician Characteristics</i>	
Physician Experience	-0.0013 * (0.0016)
Physician Case Load	0.0151 (0.0171)
Physician-patient Contact Time	-0.0015* (0.0006)
Physician Admit Rate	1.4168*** (0.2662)
Constant	-2.8948*** (0.1386)

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Table 5: Regression Results - Efficiency Model - Peer Physician

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*Dependent variable: DEA Efficiency Score*

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<i>Patient Characteristics</i>	
Avg Patient ESI Level	-0.0473 (0.0380)
Patients Over 65 Years of Age (%)	0.1052* (0.0524)
Female Patients (%)	-0.0074 (0.0525)
White Patients (%)	0.0070 (0.0976)
<i>Physician Characteristics</i>	
Physician Admit Rate	0.1922*** (0.0439)
Physician Case Load	0.0095 (0.0126)
Physician-patient Contact Time	-0.0006*** (0.0001)

Table 6: Regression Results - Effectiveness Model - Peer Physician

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*Dependent variable: DEA Effectiveness Score*

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<i>Peer Characteristics</i>	
More Efficient Peer	-0.0088 (0.0084)
More Effective Peer	-0.0371*** (0.0088)
Junior Peer	0.0159* (0.0070)
Diff Degree Peer	0.0053 (0.0197)
Diff Sex Peer	0.0065 (0.0233)
Constant	-2.7772** (0.0356)

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Table 7: Regression Results - Efficiency Model - Peer Physician

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*Dependent variable: DEA Efficiency Score*

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<i>Peer Characteristics</i>	
More Efficient Peer	-0.0197*** (0.0044)
More Effective Peer	0.0211** (0.0045)
Junior Peer	-0.0027 (0.0036)
Diff Degree Peer	-0.0030 (0.0103)
Diff Sex Peer	0.0034 (0.0123)
Constant	-2.9953*** (0.0356)

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