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Analysis of uncompensated hospital care using a DEA model of output congestion

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Abstract Uncompensated care can create financial difficulties for hospitals. The problem is likely to worsen as the number of individuals lacking health insurance continues to grow. The objective of this study is to measure how uncompensated care affects hospitals' ability to provide the services for which they do receive compensation. Applying output-based data envelopment analysis (DEA) under various assumptions on the disposability of outputs to a sample of Pennsylvania hospitals, we find that, on average, hospitals could have produced 7% more output if they had all operated on the best-practice frontier and that uncompensated care reduced the production of other hospital outputs by 2%. Thus, even if hospitals were to operate efficiently, they might still face financial distress as a result of providing uncompensated care. The findings in our study suggest that policy makers should continue looking at ways to increase funding to hospitals providing uncompensated care while not distorting economic incentives to reduce excessive costs.

Keywords Uncompensated care · Hospital efficiency · Congestion · DEA

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1. Introduction

Health care expenditures in the United States increased from $1,150 trillion in 1998 to $1,553 trillion in 2002, an increase of over 35%. During this period expenditures funded by private health insurance increased at an even faster rate — 43%. In response to this rapid growth in outlays, health insurance plans have increased both their premiums and their cost-sharing provisions [1]. The former action has made health insurance even less affordable and likely has contributed to the growth in the number of uninsured from 39.6 million in 1999 to 44.7 million in 2003. Reduced health insurance coverage, whether in the form of fewer individuals with health insurance or reduced benefits/greater cost-sharing for those who are covered by insurance, should lead to more uncompensated care—the sum of charity care and bad debts [2]. The Kaiser Commission on Medicaid and the Uninsured [3] estimated that the U.S. would spend about $41 billion for uncompensated care for the uninsured in 2004.

Uncompensated care requires the use of resources that could have otherwise been used to produce care for which compensation could have been received. This "crowding out" of compensated care, and its associated revenue, by uncompensated care represents an opportunity cost to the hospitals that provide it. Thus, uncompensated care has two costs—the direct expenses associated with the provision of uncompensated services and the indirect, or opportunity, cost of foregone compensated care. Previous research has focused on the former cost, we explore the latter.

The purpose of this paper is to apply an innovative technique to assess the impact of uncompensated care on hospitals. While this is an important issue for hospitals throughout the U.S., we focus on hospitals operating in the Pennsylvania for two reasons. First, unlike many other states, Pennsylvania has no public general hospitals to serve as "safety-nets" for the poor and uninsured [4]. Consequently, private hospitals in Pennsylvania bear a greater burden of uncompensated care than hospitals in other states. Like most states, Pennsylvania has a severe uncompensated care problem. From 2000 to 2002, expenditures for uncompensated care grew from \$872 to \$979 million. This represented 4.84% of net patient revenue in 2002 [5]. These large outlays may cause hospitals to suffer adverse fiscal consequences. For example, in 1995 the aggregate profit margin of hospitals in Pennsylvania was −2.42%. However, if uncompensated care did not exist, the profit margin would have been 1.50% [6]. Our second reason for focusing on hospitals operating in Pennsylvania is the availability of an extensive data set that identifies uncompensated care.

To measure the economic effect of uncompensated care on hospitals, we apply data envelopment analysis (DEA) to an output maximization problem to measure the efficiency with which hospitals produce their observed levels of outputs from the resources they have available. Under the output maximization approach, efficiency is measured as the maximum feasible expansion of outputs while holding the amount of inputs constant. *Ceteris paribus*, as outputs increase, revenues will also rise.

Standard DEA measures of output efficiency are based on a radial expansion of *all* outputs, which means that both "desirable" (i.e., compensated) output and "undesirable" (i.e., uncompensated) output are increased when an inefficient hospital is projected onto the efficient frontier. In contrast to the standard approach, we assume that the objective of hospitals is to maximize "good" outputs while simultaneously minimizing "bad" outputs. To assess the effect of bad outputs on the production of good outputs, we must look at the joint production of these two types of outputs in assessing the efficiency of production. This can be done by first measuring efficiency under the assumption of strong disposability of outputs (SDO), which implies that the expansion of all outputs is desirable, then by measuring efficiency under the assumption of weak disposability of outputs (WDO), which implies that the expansion of some outputs is undesirable. A comparison of the efficiency measures under these two assumptions provides a measure of the "congestion" imposed on good outputs by the presence of bad outputs.

Much of the literature on congestion addresses *input* congestion—a situation in which more inputs lead to diminished output (the converse would also be true). A standard example is that, beyond some point, adding more vehicles to a roadway reduces the flow of traffic (the inputs are vehicles and road, the output is traffic flow). Two approaches to measuring congestion exist in the efficiency measurement literature.[1] While both approaches offer means to detect and measure congestion and to identify the source of congestion, they differ in how they do so. One approach, [10], follows an axiomatic treatment of efficiency measurement and measures congestion by comparing radial efficiency measures under different assumptions on the underlying production technology. The second approach begins with an additive model of efficiency and measures congestion relative to "slacks" in production [11].

In this paper we are interested in the effects of *output* congestion, which, as noted above, is based on the idea of joint production. "Desirable" goods (in our case, compensated care) and "undesirable" goods (in our case, uncompensated care) are jointly produced. Under a given technology, the undesirable goods cannot be disposed of without incurring some cost (e.g., fines or reductions in the "good" output). As noted by Färe et al. [10], output congestion is an issue of whether outputs are strongly or weakly disposable. Hence, we pursue the approach in [10].

Treating uncompensated care as an economic "bad" may appear harsh. We do not mean to imply that the provision of uncompensated care, especially charity care, is not a good thing. Indeed, provision of charity care is part of the mission of most hospitals. Rather, we wish to make clear the fact that there is an opportunity cost associated with the production of uncompensated care—an increase in uncompensated care may jeopardize the production of compensated care and would therefore impose a cost on hospitals. Conversely, hospitals may be forced to reduce uncompensated care if they do not have enough paying patients [12, 13]. Any policy initiative concerning the provision of uncompensated care should account for these costs as well as for the financial distress that may be associated with the provision of uncompensated care. In other words, we surmise that it should be this opportunity cost that is required as payment for uninsured care from a social good framework.

The remainder of the paper is organized as follows. In the next section, we review the pertinent literature. Section 3 contains a description of the models used. The data and results are presented in Section 4. Section 5 concludes the paper.

[1] The interested reader is encouraged to examine the debate between Cooper et al. [7] and Färe and Grosskopf [8, 9] regarding the measurement congestion.

2. Literature review

Hospitals require patient revenues to cover their financial needs, which include operating expenses and growth in working capital, to provide for technological change, and to provide insulation from the effects of risk [14]. Revenue loss due to uncompensated care impinges upon the financial health of hospitals and may jeopardize their ability to carry out their mission.

Nonpayment for services contributes to the adverse trend in hospital profitability. Vogel et al. [15] found a −0.2% hospital operating margin in 1990, a decrease of 2% from 1984. These authors also found that bad debt had an elastic effect on the probability of low profitability in a hospital—as the amount of bad debt rises, the probability of low profitability in hospitals rises even faster. More recently, Rosko [4] found that profitability was negatively related to greater than average amounts of uncompensated care provided at each hospital. Before cost control measures were rigorously implemented by government and private insurers, hospitals could cross-subsidize uncompensated care. In effect, hospitals shifted the burden of non-paying patients to paying patients. This practice resulted in higher costs for third-party payers. As Medicare, Medicaid, and other third-party payers introduced fixed fee payment systems, the financial risk of producing health care shifted from payers to providers [16].

From a financial management standpoint, cuts in potential earnings may have a spillover effect coming in the form of a hospital's ability to receive approval for debt financing. The critical factor in obtaining approval for debt financing from lenders is the ability to show that a hospital can generate sufficient income and insulation from the effects of risk [17]. Even if approval is gained, a higher risk of default will cause creditors to require a higher interest rate.

It is clear from the previous research that uncompensated care can have a deleterious effect on a hospital's financial viability. We plan to add to this research by assessing how uncompensated care affects hospitals in real resource terms; i.e., what does a hospital give up to provide uncompensated care?

3. Modeling

To assess the effect of uncompensated care on hospitals, we employ data envelopment analysis (DEA). The basis of DEA stems from the works of Debreu [17] and Farrell [18] and is a non-stochastic, non-parametric estimation of an organization's (in this case, a hospital's) efficiency; the efficiency scores produced by DEA are often referred to as measures of "Farrell Efficiency." Under this approach, multiple inputs and multiple outputs are used to construct a piece-wise linear "best-practice" frontier. DEA derives the best-practice frontier by solving linear programming problems. The efficiency of an individual hospital is then gauged by its position relative to the best-practice frontier. Since the best-practice frontier likely diverges from the true underlying production frontier, the DEA relative efficiency measures can be thought of as lower bounds on the actual level of inefficiency present among the hospitals in our sample.

In our analysis we use output-based measures of efficiency. This involves adjusting output levels while holding inputs and technology constant. The output-orientation was selected because we seek to maximize the number of patient days and outpatient visits that could be produced given the inputs available. The initial DEA model we use produces radial measures of efficiency in that the output vectors are expanded along rays through the origin (i.e., outputs expand equiproportionately). A score of 1.00 indicates that the firm is output-based efficient; a score greater than one indicates the possible increase of production of all outputs. We also use a non-radial DEA model that treats a subset of outputs as desirable (i.e., strongly disposable) while treating a second subset of outputs as undesirable (i.e., weakly disposable).

There are several benefits of using DEA for assessing hospital performance. For a review of this literature see Hollingsworth [19] or Worthington [20]. First, this approach can accommodate the multiple inputs and multiple outputs that characterize hospital production; this multiplicity, especially on the output side, is not as readily accommodated in econometric models of production. Second, unlike parametric methods, this methodology does not require the imposition of a particular functional form on the relationship between inputs and outputs. Third, this approach requires only quantity data, which are readily available in the case of hospitals, rather than price data which are less readily available and may not be accurate when they are available. A drawback of the DEA methodology, as it is commonly implemented, is that there is no allowance for "noise." As a result, all deviations from the frontier are typically

[2] A variety of methods for accounting for noise in DEA are available; see Simar and Wilson [21], Ray [22; chapter 12], and Cooper et al. [23; chapter 9] for overviews. One approach is to bootstrap efficiency measures. However, a bootstrap procedure for a model with weak disposability is likely more complicated than the procedure prescribed by Simar and Wilson [24] due to the non-linear boundary of the production set and has not yet been developed. We thank Paul Wilson for pointing this out to us.

attributed to inefficient performance.[2] On balance, DEA is a very useful tool for analyzing performance and has been applied in numerous studies of hospital efficiency.

In the non-parametric production model, we begin with vectors of outputs $y = (y_1,..., y_m)$ and inputs $x = (x_1,..., x_k)$ for each of N observations. Production technology is represented by the output correspondence which is the set of all output vectors y that are producible from the input vector x:

$$P(x|V,S) = \left\{ y : y \leq z \cdot M, z \cdot K \leq x, z \in \Re, \sum_{j=1}^{N} z_j = 1 \right\}, \tag{1}$$

where M is a matrix containing the m outputs of each of the N hospitals in the sample, K is a matrix containing each of the k inputs for each of the N observations, and z denotes a vector of intensity variables (i.e., weights that form convex combinations of observed inputs and outputs), V indicates that the productive technology exhibits variable returns to scale (VRS) (the summation restrictions on the elements of z allows for VRS in the technology), and S denotes that strong disposability of outputs (SDO) is asssumed [10].

The assumption of SDO implies that all outputs are "desirable." However, we can also define a technology in which some of the outputs may be "undesirable;" this requires relaxing the SDO restriction for the undesirable outputs. An output correspondence that allows for weak disposability (WDO) of some outputs and SDO of other outputs is given by:

$$P(x|V,W/S) = \left\{ \left(y^w, y^S\right) : y^W \leq \mu \cdot z \cdot M^W, y^S \leq z \cdot M^S, \right. \\ \left. z \cdot K \leq x, 0 \leq \mu \leq 1, z \in \Re, \sum_{j=1}^{N} z_j = 1 \right\}, \tag{2}$$

where M^W and M^S are matrices containing the weakly and strongly disposable outputs, respectively, of all N hospitals in the sample. The technologies $P(x|V,S)$ and $P(x|V,W/S)$ differ in their assumptions on the disposability of outputs; the former assumes that all outputs are strongly disposable, while the latter assumes that some outputs are weakly disposable (y^W) and that others are strongly disposable (y^S). The scaling factor, μ, in Equation (2) allows for weak disposability of the undesirable outputs [25]. This difference allows us to gauge the loss of "desirable" output due to production of "undesirable" outputs; i.e., output congestion [10].

To determine the measures of output-based efficiency under the assumptions of both strong and weak disposability of outputs, we must solve a series of linear programming problems. First, to obtain the Farrell output-based efficiency measure under SDO, the following linear programming problem must be solved once for each observation:

$$\begin{aligned} F_o(x, y/V, S) = \max_{z,\theta^S} \theta^S & \\ s.t.\ \theta^S \cdot y &\leq z \cdot M \\ z \cdot K &\leq x \\ z &\in \Re_N \\ \sum_{j=1}^{N} z_j &= 1. \end{aligned} \tag{3}$$

The solution to Equation (3), $\theta^{S*} \geq 1$, gives the maximum feasible radial expansion of all outputs given the best-practice frontier for the particular hospital for which the linear program has been solved. Note that $(\theta^{S*} - 1) \times 100\%$ gives the percentage increase in all outputs that would occur if a hospital were to move from its observed level of outputs to the best-practice frontier under the assumption of SDO.

Next we calculate an output-based efficiency measure under the assumption of WDO of the undesirable output (i.e., uncompensated care) and SDO of the desirable outputs (i.e., compensated care) by solving the following linear programming problem once for each of the hospitals in the data set:

$$\begin{aligned} F_o(x, y|V,W/S) = \max_{z,\theta^{W/S}} \theta^{W/S} & \\ s.t.\quad \theta^{W/S} \cdot y^W &\leq \mu \cdot z \cdot M^W \\ \theta^{W/S} \cdot y^S &\leq z \cdot M^S \\ z \cdot K &\leq x \\ 0 \leq \mu &\leq 1 \\ z &\in \Re_N \\ \sum_{j=1}^{N} z_j &= 1 \end{aligned} \tag{4}$$

The solutions to these two linear programming problems are used to calculate output congestion; specifically:

$$C_o(x, y|V) = \frac{F_o(x, y|V, S)}{F_o(x, y|V, W/S)} = \frac{\theta^{S*}}{\theta^{W/S*}} \geq 1 \tag{5}$$

If the efficiency measures for a hospital are equal under both technologies (i.e., $C_o(x, y|V) = 1$), then there is no output congestion. However, if an observation is more technically efficient relative to the WDO technology vis-à-vis the SDO technology (i.e., $C_o(x, y|V) > 1$), then output congestion exists.

Congestion is just one way in which inefficiency can arise, leading to a reduction in output. The total output

Table 1 Descriptive statistics of the data

	Mean	Std. Dev.	Minimum	Maximum
Inputs				
Beds	215.13	169.774	20	1,285
Registered nurses	285.04	308.073	16	2,234
Licensed practical nurses	33.05	27.279	1	149
Residents	35.62	117.070	0	893
Other labor	806.19	880.349	60	7,448
Outputs				
Inpatient surgeries	2,998.29	3,363.817	55	23,747
Outpatient surgeries	5,366.67	4,213.469	150	24,361
Emergency visits	28,030.79	18,951.370	63	101,391
Outpatient visits	144,176.11	143,623.08	232	846,57
Adjusted inpatient days	81,170.99	95,425.10	2,815.53	795,169.77
Uncompensated care (0,000s)	512.617	824.02	14.5	7,680.6

lost due to technical inefficiency is given by a measure of overall technical efficiency; overall technical inefficiency is the results of the combination of "pure" technical inefficiency, scale inefficiency, and congestion inefficiency. We calculate all four efficiency measures—overall technical, pure technical, scale, and congestion—for two reasons. First, we are interested in the relative magnitude of the efficiency due to congestion and other sources. Second, while congestion directly reduces efficiency if it exists, it may also reduce efficiency indirectly by leading to reductions in the other types of efficiency [26]. We therefore compare the levels of the other three efficiency scores across congested and uncongested hospitals.

Overall technical efficiency is measured relative to a technology characterized by SDO and constant returns to scale (CRS); pure technical efficiency is measured relative to a technology that features SDO and variable returns to scale (VRS); scale efficiency is given by the ratio of the overall efficiency score to the pure technical efficiency score; congestion is given by Equation (5).

4. Data and results

4.1. Data sources

This study is based on cross-sectional data for all (N = 170) Pennsylvania short-term, general, community hospitals for which complete 2002 data were available. The unit of analysis is the hospital. Limiting the analysis to one state avoids the confounding effects of state policy on the provision of uncompensated care. It also allows for a more consistent definition of uncompensated care. Further, Pennsylvania mandates public disclosure of hospital data, including uncompensated care statistics.

The primary sources of data are the Pennsylvania Health Care Cost Containment Council [5] (uncompensated care), the American Hospital Association's *Annual Survey of Hospitals* (inputs, outputs, and hospital characteristics), and the Center for Medicare and Medicaid Services (Medicare Case Mix Index). The inputs included: beds, registered nurses, licensed practical nurses, residents, and other labor. The following outputs were used: inpatient surgeries, outpatient surgeries, emergency visits, non-emergency outpatient visits, adjusted inpatient days, and uncompensated care. We adjusted inpatient days by multiplying them by the value of the hospital's Medicare Case Mix Index (MCMI) [27]. This reflects cost variations associated with case-mix complexity. The MCMI is an index whose weights reflect the relative costliness of diagnostic related groupings (DRGs) into which the hospital's patients have been classified. Ideally, an all-payer case-mix index would be used; however, this was not available.[3] A study of Pennsylvania hospitals found that the MCMI is highly correlated ($r > 0.90$) with a DRG case-mix index based on all patients [28]. Table 1 provides a list of the variables used in the analysis and their descriptive statistics.

The PHC4 defines uncompensated care as the sum of charity care and bad debts for all services provided by the hospital. This is consistent with previous research studies (e.g. [2], [4], [12]) and it avoids the problem of different definitions of charity care and bad debt by combining the two. Charity care includes the value of services provided to patients who, as deter-

[3] Our models were calculated using data that were adjusted for case-mix as well as the original, unadjusted data. The results for the two sets of data were qualitatively indistinguishable. The lack of a "case-mix effect" may be due to the fact that only one of seven inputs was affected by the adjustment for case-mix.

Table 2 Descriptive statistics efficiency scores

Efficiency score	Mean	Std. Dev.	Minimum	Maximum
Overall technical efficiency	1.07	0.12	1.00	1.71
Pure technical efficiency	1.05	0.09	1.00	1.64
Scale efficiency	1.02	0.06	1.00	1.33
Congestion efficiency	1.02	0.004	1.00	1.28

mined by the hospital, cannot afford to pay their entire bill. Hospitals report charity care at full charges based upon their charge schedule. However, the PHC4 adjusts this to a revenue basis to reflect the amount the hospital would have received if it were paid the average of what it received from all payors during the year. Bad debt expenses occur when the hospital expects the patient to be able to pay for services but later determines that all or a portion of the bill is uncollectible. Hospitals do not report the extent to which bad debt is booked at full charges. Accordingly, the PHC4 is not able to make the same type of revenue adjustments it makes for charity care.

4.2. Results

Table 2 presents the descriptive statistics for our output-based efficiency scores. We find that, on average, the Pennsylvania hospitals in our sample could have produced 7% more output, without using any additional inputs, if they had operated on the best-practice frontier. Compared with other DEA studies of U.S. hospital efficiency, we have found a rather high level of efficiency. This may in part be due to the fact that our data set includes hospitals from just one state whereas most studies include hospitals from throughout the U.S.; thus, the hospitals in our sample may be more similar in terms of operating performance than might be the case in other studies. Recalling that DEA produces relative efficiency scores, the level of actual inefficiency is likely more than 7%.

Most of the measured inefficiency can be attributed to pure technical inefficiency, which averaged 5%; scale inefficiency and congestion inefficiency, due to the provision of uncompensated care, each averaged 2%. The last result suggests that the production of uncompensated care reduces the production of compensated care, and its associated revenue, by 2%. Given that uncompensated care is a small part of a typical hospital's total care, the fact that it was found to reduce compensated care by even 2% suggests that uncompensated care has a high degree of "leverage." The revenue loss associated with the congestion inefficiency is potentially the difference between a net profit and a net loss for hospitals—recall that Rosko [6] found that without uncompensated care, hospitals would have had positive rather than negative profit margins.

We are also interested in whether the effect of uncompensated care, as measured by congestion efficiency, differs across different types of hospitals—namely, urban vs. rural hospitals, teaching vs. non-teaching hospitals and NFP vs. for-profit hospitals. To do so, nonparametric tests are performed on the mean congestion efficiency scores of hospitals with the different characteristics just mentioned. Results of these tests are reported in Table 3. Despite the large metropolitan areas of Pittsburgh and Philadelphia, Pennsylvania is one of the most rural states in the U.S. While congestion appears to be a larger problem for rural hospitals in Pennsylvania (see Table 3), the observed difference in the mean congestion efficiencies of rural (1.04) and urban (1.01) hospitals is only marginally statistically significant. The teaching hospitals (mean congestion efficiency of 1.07) in our study appear to bear significantly more of the economic costs due to congestion of uncompensated care than do non-teaching hospitals (mean congestion efficiency of 1.01), suggesting that teaching hospitals not only incur the social costs of teaching, but also for providing uncompensated care. Not surprisingly, NFP hospitals (mean congestion efficiency of 1.05) have a bigger opportunity cost associated with the provision of uncompensated than do for-profit hospitals (mean congestion efficiency 1.00), which appear to be uncongested. While the provision of uncompensated care (at least when it is charity care) is a part of NFPs' mission, our results suggest that this mission has a real cost, perhaps justifying the NFPs' tax exempt status.

Finally, we are interested in whether the other efficiency measures vary across congested and non-congested hospitals. As noted earlier, the reason for

Table 3 Congestion efficiency by hospital characteristics

Hospital characteristics	Congestion efficiency	Wilcoxon score	Kruskal-Wallis
Rural	1.04	1.24*	1.54
Urban	1.01		
Teaching	1.07	2.71***	7.06***
Non-teaching	1.01		
For-profit	1.00	1.92**	3.72**
Not-for-profit	1.05		

*Statistically significant at the 10% level.
**Statistically significant at the 5% level.
***Statistically significant at the 1% level.

Table 4 Differences in mean efficiency scores across congested and uncongested hospitals

Efficiency measure	Means for uncongested hospitals	Means for congested hospitals	Wilcoxon score	Kruskal-Wallis
Overall technical efficiency	1.04	1.19	8.67***	75.23***
Pure technical efficiency	1.01	1.16	5894.00***	103.84***
Scale efficiency	1.02	1.03	4.74***	22.44***

***Statistically significant at the 1% level.

doing this is that congestion may indirectly affect other aspects of managerial efficiency [26]. For our sample, congested hospitals are less efficient than non-congested hospitals with regard to the other three efficiency measures. As shown in Table 4, there are sizable and statistically significant differences in the overall technical efficiency and pure technical efficiency scores of hospitals with and without congestion associated with uncompensated care. While the difference in mean scale efficiencies is also statistically significant, the actual difference is rather small. Overall, these findings suggest that managerial efficiency is affected by the crowding out associated with the provision of uncompensated care, which in turn could affect hospitals' financial viability, *ceteris paribus*.

5. Conclusion

Using an innovative DEA technique we measured the congestion inefficiency associated with hospitals' provision of uncompensated care. This approach reveals the opportunity cost, as opposed to simply the accounting cost, of providing uncompensated care.

For our sample of Pennsylvania hospitals, we found that hospitals could have produced 7% more output had they operated on the best-practice frontier. Whereas this may appear to be a rather small amount of inefficiency given the notoriously high cost of health care in the U.S., it must be remembered that DEA produces relative efficiency measures which can be viewed as a lower bound on the true level of inefficiency for hospitals in our sample. Similarly, the congestion associated with uncompensated care (also a relative measure) was responsible for decreasing compensated care by 2%, on average, for the hospitals in our sample. Thus, the provision of uncompensated care directly and indirectly affects the financial performance of hospitals; directly because care is provided for which compensation is not received and indirectly through the congestion that reduces the levels of the compensated care that can be provided, i.e., part of the opportunity cost of uncompensated care is foregone compensated care. Furthermore, hospitals that experienced congestion had lower levels of technical efficiency than those hospitals that were free of congestion.

As is always the case, some caveats apply to our study. First, since we do not analyze any financial data, the detailed effects of congestion on the financial health of the hospitals in our sample cannot be traced. However, the social costs borne by private hospitals in the face of congestion can be assessed. Since there is no public provision of hospital care (i.e., local public hospitals) in Pennsylvania, the government is "obligated" to subsidize the social good since it may be assumed that the private sector would not otherwise provide enough of it. Hence, we may not know the true amount of uncompensated care that should be provided since hospitals may reduce the provision if it compromises financial health. Second, our specifications of outputs include both services provided as well as a monetary value of uncompensated care. While it might be argued that uncompensated care may not be separable by service, it does not matter for our purposes. We are interested in determining the efficiency with which all services are produced, which means that all outputs could expand radially if a hospital is inefficient.[4] Third, our data do not differentiate between charity care and bad debt. If the congestion were wholly comprised of bad debt, then hospitals could correct the loss of revenue through greater managerial efficiency; i.e., better debt-collection efforts. On the other hand, if the congestion were wholly charity care, some type of government policy to support the provision of this social good would be called for. The 2% average level of congestion, as measured here, thus serves as an upper bound for the government subsidy to account for social cost created by the congestion pending appropriate accounting information.

By identifying the separate costs due to uncompensated care and technical inefficiency, our approach demonstrates the application of a managerial or policy method that may reveal the true nature of hospital losses and identify the differences in terms of real

[4] We thank an anonymous referee for this comment.

resources lost. Even though our results are suggestive that resource loss is incurred, we feel this method has the potential for capturing the explicit and implicit costs of uncompensated care. This technique might have other important applications in the analysis of other sources of output congestion. These include the provision of poor quality of care (i.e., unexpected mortality) or unneeded care (i.e., re-admissions, extra tests and procedures, unnecessary inpatient days).

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