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Are Hospitals Seasonally Inefficient? Evidence from Washington State Hospitals

By

Daniel L. Friesner, Matthew Q. McPherson, and Robert Rosenman

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Daniel L. Friesner [a]
Matthew Q. McPherson [a]
Robert Rosenman [b]

[a] School of Business Administration
Gonzaga University
502 East Boone Ave.
Spokane, WA 99258-0001
Telephone: (509) 323-3415
Fax: (509) 323-5811
Email: friesner@jepson.gonzaga.edu

[b] School of Economic Sciences
Washington State University
Hulbert Hall
Pullman, WA 99164-6210

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Abstract

Efficiency measurement has been one of the most extensively explored areas of health services research over the past two decades. Despite this attention, few studies have examined whether a provider's efficiency varies on a monthly, quarterly or other, sub-annual basis. This paper presents an empirical study that looks for evidence of seasonal inefficiency. Using a quarterly panel of general, acute-care hospitals from Washington State, we find that hospital efficiency does vary over time; however, the nature of this dynamic inefficiency depends on the type of efficiency being measured. Our results suggest that technical and cost efficiency vary by quarter. Allocative and scale efficiency also vary on a quarterly basis, but only if the data are jointly disaggregated by quarter and another, firm-specific factor such as size or operating status. Thus, future research, corporate decisions and government policies designed to improve the efficiency of hospital care need to account for seasonal trends in hospital efficiency.

Introduction and Literature Review

Over the past two decades, efficiency measurement has been one of the most intensely explored areas of health services research. According to one article, over 91 efficiency studies were published in peer-reviewed journals as of 1997 (Hollingsworth et al 1999). By the end of 2002, this number was in excess of 188 (Hollingsworth 2003).

In general, research on efficiency measurement in health care focuses on three key issues. One issue is the approach used to generate efficiency scores. The two most commonly used approaches are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (Hollingsworth 2003). Both are similar in that efficiency is measured relative to a best practice (or efficient) frontier. Deviations from this frontier (usually measured as a geometric distance) give measures of (relative) efficiency.[1] A large literature has developed comparing the two techniques and examining their statistical properties. Examining the statistical properties of DEA efficiency estimates, in particular, has encompassed a significant portion of the recent literature (see, for example, Banker, 1993: Burgess and Wilson, 1998; Simar and Wilson, 2000 and 2003; and Murillo-Zamorano, 2004).

[1] The primary difference between SFA and DEA lies in how the efficient frontier is calculated. SFA employs regression analysis to estimate the efficient frontier, and calculates individual efficiency scores by decomposing the error term of the regression equation. Because regression analysis is used, the efficiency scores can be analyzed using standard statistical techniques. However, a drawback to SFA is that the results may be subject to parametric specification bias; if one miss-specified the regression equation, the efficiency scores will be biased. DEA uses linear-programming methods to calculate both the efficient frontier and the efficiency scores. The advantage of DEA is that it is nonparametric in nature; that is, it does not require the researcher to specify a functional form for the production process being analyzed. Unlike SFA, DEA also allows the researcher to simultaneously examine several different types of efficiency (including technical, allocative, cost and scale), and allows for the specification of multiple outputs, especially when calculating technical and scale efficiency. A potential drawback is that DEA-generated efficiency scores are usually not normally distributed, and thus cannot be analyzed with standard, parametric hypothesis tests.

The second major area of research uses one of these two approaches to examine efficiency in a single area of health care production.[2] Such studies have covered virtually every area of health care, including hospitals, nursing homes, dental services, pharmacies, organ procurement, stroke treatment and neonatal care. These studies look for systematic differences in efficiency across firms, patients or other decision-making units, and try to identify the factors causing (or correlated with) those differences (Hollingsworth 2003). For example, in the US hospital efficiency literature, studies have examined whether for-profit hospitals are more or less efficient than private, nonprofit or government-owned hospitals (Valdmanis 1992; Zuckerman et al 1994; Ozcan et al 1996; Folland and Hofler 2001; Li and Rosenman 2001). Similar studies have also been conducted on US for-profit and nonprofit nursing homes (Chattopadhyay and Ray 1996; Ozcan et al 1998; Rosko et al 1995). In addition, whether significant efficiency differences exist between single specialty physician practices and those with a large number of different physician specialties (Defelice and Bradford 1997; Rosenman and Friesner 2004) have been examined.

A third area of research uses a combination of different efficiency calculations to measure other aspects of health care practice. An extensive literature uses technical efficiency calculations to create Malmquist indices of technological change (Hollingsworth 2003). Other studies (Fare et al 1995; Maniadakis et al 1999; Sola and Prior 2001) have used technical efficiency scores to create indices of quality change.

Most efficiency studies in health care use annual data (usually in cross-sectional or panel form), implying that efficiency scores are long-run in nature. However, studies in other fields, particularly those in banking and financial markets, have begun analyzing differences between

[2] Several studies utilize both SFA and DEA; for example, see Bryce et al 2000, Giuffrida and Gravelle 2001, Jacobs 2001 and Rosenman and Friesner 2004.

short-run and long-run firm efficiency (Prior 2003; Barua et al 2004). Several studies specifically analyze firm efficiency using monthly and quarterly data, and find evidence that efficiency does vary by season (Golany and Storbeck 1999; Zenios et al 1999).

Seasonal efficiency may have several causes, including capacity utilization (Fare et al 1994; Kerr et al 1999), where, in order to meet peak demand, firms invest in (quasi-fixed) inputs that may not be used efficiently (or produce an efficient amount of output) during non-peak seasons,[3] and input price variations, where firms cannot react quickly enough to price changes causing allocative (and potentially cost) inefficiency. The higher or more pronounced the variation, the more one might expect variations in efficiency to occur. Sengupta (1998) makes a similar argument for output price fluctuations.

There is some evidence that many health care providers, including hospitals, may exhibit behavior that could result in sub-annual changes in efficiency. Friedman and Pauly (1981) used quarterly data and found that nonprofit hospitals over-invest in capital to meet unanticipated changes in demand. Jack and Powers (2004) provide a case study demonstrating how health care providers can use volume flexibility to better match input procurement and usage with fluctuations in patient demand.

While these studies are useful, they suggest behaviors but provide limited insight.[4] Given the myriad of changes in the hospital industry over the last several decades (including the HMO revolution and the introduction of prospective payment) it is plausible that hospitals in today's economic environment respond more quickly to changing demand conditions, thus seasonal changes in demand may not induce inefficiency.

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[3] Generally these inputs are capital goods. However, in certain instances – for example, if the firm has a binding contract with a labor union – other inputs such as labor may also exhibit seasonal under-utilization.

[4] The Pauly (1981) study is over two decades old, and the Jack and Powers (2004) analysis is a single case study.

An issue related to seasonal efficiency is the orientation used in its measurement. Traditional (DEA-based) excess capacity studies assume that production is output oriented; that is, providers use a fixed set of inputs to produce as much output as possible (Fare et al 1994; Fare et al 2000). However, at least in the short-run, it is likely that many health care providers treat an exogenously determined level of output using as few inputs as possible (i.e., an input-oriented production process) (Fare et al 1995; Maniadakis and Thanassoulis 2000; Rodriguez-Alvareza et al 2004). Thus, in health care, capacity utilization may not be an appropriate measure.

Another concern is the type of seasonal inefficiency. It is possible that findings of seasonal variations in efficiency can depend on the type of efficiency being analyzed. For example, firms may exhibit seasonal variations in allocative efficiency, but not in scale efficiency. To our knowledge, none of the studies discussed above (including those in the banking and finance literature) have examined this issue empirically.

A final question is whether or not it is possible to predict seasonal efficiency changes (if they exist). The hospital industry is unique in that demand fluctuations depend crucially on demographic and epidemiological changes. These changes may vary by season, but not necessarily in a constant, predictable fashion. This, in turn, may also lead to unpredictable changes in seasonal efficiency.

In this paper we perform an empirical analysis of these issues. Using a quarterly panel of hospitals over a four-year period, we investigate whether hospitals exhibit seasonal variations in efficiency. We also look separately for evidence of seasonal variations in technical, allocative, cost and scale efficiency. Finally, we consider some evidence about whether certain times of the year consistently exhibit relatively more or less efficiency, on average, than other quarters. This, in turn provides some evidence about whether seasonality (if it exists) occurs in a predictable fashion.

In the next section, we present our empirical methodology, including a formal discussion of our testable hypotheses. Next, we describe the data used in our study. We then present and discuss the results of our analysis, and conclude our paper by discussing the implications of our work and presenting some suggestions for future research.

Empirical Methodology

A Graphical Description of Seasonal Inefficiency in Hospitals

We illustrate seasonal efficiency using the simple case of a firm that produces a single output (Q) with two inputs, capital (K) and labor (L).[5] Assume that the production process is input oriented; the firm chooses K and L to produce an exogenously determined level of output, and that there are two seasons: a high demand season (S^{high}) and a low demand season (S^{Low}).

The isoquant I^{high} depicted in Figure 1 gives the technically efficient ways of producing the good when demand for Q is high. The tangent between I^{high} and the isocost curve (C^{high}) depicted by point A gives the allocative and cost efficient level of production during the peak season.[6] Point B, the tangent point between isoquant I^{low} and isocost C^{low}, indicates the efficient level of resource usage during the off-peak season. Assuming that at least as much output is produced in the high demand season as the low demand season, I^{high} should always be at least as far from the origin as I^{low}, and similarly for C^{high} and C^{low}. If seasonal variation in outputs, inputs and input prices is absent, then $I^{high} = I^{low}$, $C^{High} = C^{low}$ and A and B are identical.

[5] Expanding this argument to include multiple inputs, outputs or seasons should not significantly impact our analysis, as doing so merely adds extra dimensions to Figures 1 – 3.

[6] By definition, cost efficiency is the product of allocative and technical efficiencies. Thus, if a firm is cost efficient it is also allocatively and technically efficient.

However, if there are factors that influence efficiency across the two seasons, then most likely A and B (and the isoquants, isocost lines or both) will not be identical, creating the possibility of seasonal inefficiency. This is especially true if the firm purchases inputs during the peak season, and cannot change resource usage (or change it quickly enough) when demand falls. In this case the firm is seasonally inefficient because it employs $K^{high} - K^{low}$ units of excess capital and $L^{high} - L^{low}$ units of excess labor.

There are several potential causes of seasonal inefficiency, each of which may be captured by a different efficiency measure. Holding input prices constant, changes in demand may induce technical inefficiency, especially when firms over-invest in fixed inputs (or inputs that are variable, but do not change quickly enough to match demand fluctuations) to meet seasonal changes in demand. Points A and F in Figure 1 depict an example of such an occurrence. In order to meet demand during the peak season efficiently, the firm must operate at point A, acquiring K^{high} units of capital and L^{high} units of labor. However, if demand falls and resource utilization does not change, the firm will exhibit technical inefficiency because it should now be operating at point F – the radial projection of A to the origin through the lower isoquant. In relative terms, this inefficiency (or distance function) can be expressed by the ratio 0F/0A.[7]

Depending on the expansion path, seasonal changes in demand can create allocative inefficiency as well. At the new, lower level of output the firm achieves allocative efficiency at point B - the tangent between the isoquant and the lower isocost line. Holding constant the level of technical efficiency (which is measured by the proportional distance from point A to F), allocative inefficiency is illustrated by the ratio 0E/0F. As noted earlier, cost efficiency is the

[7] By definition, all distance functions are bounded between zero and one, with one representing a completely efficient firm and zero representing a completely inefficient firm. Thus, for example, if the ratio 0F/0A is 0.8, then we say that the firm in question is 80% technically efficient.

product of technical and allocative efficiency. Thus, in relative terms, total (cost) efficiency is given by (0F/0A)*(0E/0F) = 0E/0A, while cost *in*efficiency is one minus this number.

Fluctuating input prices can also induce seasonal inefficiency. If firms do not respond to these changes in a rapid manner, then firms may lose allocative and cost efficiency. Figure 2 presents an example of this phenomenon. If there is no seasonal variation in input prices (or if the firm can adjust to these prices) then point A represents the cost efficient point of production. However, if the price of capital rises (holding all else constant), then the isocost curve will rotate down, and the new efficient point will be at B. If the firm does not respond (quickly) to this change so resource utilization remains at point A, it will exhibit both allocative and technical (and, by definition cost) inefficiency, even if the expansion path is linear. Technical efficiency is given (in relative, or distance function terms) by the ratio 0E/0A, while allocative efficiency is given by the ratio 0D/0E. Cost efficiency is the product of the two measures, and is represented by the ratio 0D/0A. Clearly, the amount of technical, allocative and cost efficiency that occurs depends crucially on the magnitude of the price change, the firm's ability to respond to this change and the firm's initial resource allocation (i.e., whether the firm is initially efficient or inefficient). In fact, under special circumstances it is conceivable that fluctuations in input prices may cause only technical inefficiency, only allocative inefficiency or both.

In addition to technical, allocative and cost efficiencies, seasonality may also affect scale efficiency. Figure 3 presents a simple graphical examination of seasonal scale efficiency using a single output (for example, adjusted patient days) and a single input (physician FTEs).[8] Two productions frontiers are shown; one assuming constant returns to scale (CRS) and one assuming variable returns to scale (VRS). As in the previous two figures, the firm is technically efficient if it chooses its input (and consequently its output) such that the point of production is on the

[8] The same interpretation discussed in footnote 5 also applies here.

frontier.[9] Scale efficiency implies that the firm can gain efficiency by altering the size of its production process. Increasing returns to scale imply that the firm can gain efficiency by increasing production of Y (which generally occurs when producing on the bottom portion of Figure 3), while decreasing returns imply that a reduction of scale increases efficiency (which occurs on the upper portion of Figure 3). If one is producing optimally, then, there is no efficiency gain by changing the scale of production. By definition, this implies producing at point A, where the two frontiers are tangent.

In relative terms, scale efficiency can be measured by the ratio of the efficiency scores based on the CRS and VRS frontiers. For example, if the firm operates at point B, scale efficiency is given by the ratio $\left(\frac{B_0 B_{crs}}{B_0 B}\right) \Big/ \left(\frac{B_0 B_{vrs}}{B_0 B}\right) = \frac{B_0 B_{crs}}{B_0 B_{vrs}}$. As this ratio approaches one, the firm becomes more scale efficient, and production moves from point B to point A.

Scale efficiency can also exhibit seasonality. Suppose that point A in Figure 3 represents the firm's production during the high-demand season. If demand changes and the firm does not adjust its resource usage, then the firm will move away from point A, for example, to point B. In this case, the firm is not only technically inefficient under either CRS and VRS technologies, but the scale of operations is now smaller than that necessary to be fully efficient.

Developing the Testable Hypotheses

The discussion above gives some examples of why hospitals may be seasonally inefficient. The empirical problem is how to measure this inefficiency. If hospitals are

[9] Measuring technical efficiency in this case depends on the returns to scale. Point A is efficient regardless of whether one assumes VRS or CRS. Point B leads to inefficiency regardless of the frontier chosen. Under CRS, inefficiency is given by the ratio B0Bcrs/B0B, while under VRS, inefficiency is given by B0Bvrs/B0B.

seasonally inefficient, an efficient frontier for each season can be calculated, and each hospital within a particular season can be compared to that specific frontier. Moreover, if firms are seasonally inefficient because some inputs are fixed (or if firms can adjust inputs, but not very quickly), then one can adjust the technique used to calculate the efficiency scores, particularly if these scores are calculated via DEA (Banker and Morey 1986).

Given the paucity of empirical evidence on the subject, we take a parsimonious approach and postulate a null hypothesis of no mean (or median) differences in efficiency by season (or other factors). Under this hypothesis, the frontier against which firms are measured does not change by season. Moreover, this single efficiency frontier should be comprised of a relatively equal number of firms from each season. Rejecting this hypothesis implies that, on average, firms are more or less efficient in some seasons than in other seasons, implying that seasonal inefficiency exists. In other words, there are a disproportionate number of firms in a particular season(s) that are on the efficient frontier.[10]

Another benefit of using this null hypothesis is that it allows us to abstract from the issue of non-discretionary inputs (Banker and Morey 1986). As discussed previously, failure to adjust inputs to account for output demand and input price fluctuations is one of the potential causes of seasonal inefficiency. However, under our null hypothesis, firms (on average) can either adjust all inputs, or have (quasi) fixed inputs. The fixed nature of these inputs affects firms equally (on average) over time. In either case, one can use traditional methods of calculating (DEA) efficiency scores which generally assume all inputs are discretionary.[11] Because we have

[10] Given that one can reject, but never accept a null hypothesis, this specification also allows us to make a stronger conclusion about whether hospitals are seasonally inefficient.

[11] An additional argument for allowing all inputs to be discretionary is that we have no a priori reason to believe that one type of input (for example, capital) is more likely to lead to seasonal inefficiency. This is especially true given the fact that the data used in this study are quarterly in nature. Had we used data of shorter frequency (for example, monthly data) this assumption would be less likely to hold. At the same time, this also implies that one is more

identified several types of efficiency, we test this general hypothesis four times, once for each type of efficiency: technical; allocative; cost; and scale.

Empirical Techniques

We implement our analysis using a three-step approach. First, we estimate efficiency scores using DEA. We chose DEA over alternative techniques such as SFA not only because DEA is more widely used, but also because DEA more easily allows for the calculation of multiple efficiencies, particularly scale and allocative efficiencies. DEA scores were calculated using DEAP Version 2.1.[12] This program calculates all necessary (input-oriented) DEA efficiency scores, as well as supporting information such as slack and target input values using a multi-stage approach.

Once the efficiency scores have been calculated, we use nonparametric hypothesis tests to look for average differences in efficiency by time period. The data used in this study cover sixteen consecutive quarters. As such, we not only look for average efficiency differences by quarter, but also by year. Looking at efficiency scores by quarter provides an indication of a predictable seasonal pattern, while looking at efficiency scores by year would miss any seasonal pattern. We utilize two nonparametric tests; the Kruskal-Wallis test is used to examine mean differences in efficiency over time and the sign test is used to detect median differences.

One complicating factor is that hospitals vary widely in size, location and tax status – all of which may influence dynamic efficiency. For example, small, rural hospitals may have smaller populations from which to acquire labor and reduced access to reasonable financing, as

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likely to find evidence of seasonal inefficiency as the frequency of the data is shorter. We leave this possibility as a suggestion for future research.

[12] This program was written by Tim Coelli and is available from the Center for Efficiency and Productivity Analysis at the University of Queensland in Australia. The program can be downloaded at http://www.uq.edu.au/economics/cepa/index.htm.

compared to larger, urban hospitals. Small, rural hospitals may also be the exclusive source of medical care for their communities, and thus may be more affected by changing epidemiological conditions. Demand over a smaller population can vary more over seasons, as there is less smoothing across patients and illness categories. As such, these hospitals may be more prone to scale and allocative inefficiency (and thus seasonal variations in scale and allocative efficiency) than larger (usually urban) hospitals. To check for this possibility, we conduct the sign and Kruskal-Wallis tests, simultaneously decomposing time and each of these factors.[13]

Data

The data used in this study consist of Washington state, acute-care, hospitals. Each quarter, hospitals in the state are required to certify and submit a report to the Washington State Department of Health (DOH) containing basic financial and utilization data. The data used in this study come from these reports for the years 1998 – 2001. There are 87 non-specialty, non-HMO hospitals in the complete sample. After eliminating observations that provided missing or unreliable data, we were left with a sample of 80 hospitals and 1076 observations. Observations were eliminated because the hospitals in question did not treat a minimum number of patients within each output category, implying that excluded hospitals tended to be smaller and located in rural areas.[14] Of the 80 hospitals included in the final sample, 4 hospitals are for-profit, 36 are private, non-profit and 40 hospitals are government (community, district or state) owned. The

[13] A common approach in the literature is to use Tobit regressions to see how different hospital characteristics affect efficiency. However, recent work by Simar and Wilson, (2000, 2003) among others has demonstrated that such estimates (whether estimated with a Tobit model or other maximum likelihood approaches) are biased and very likely inconsistent. Thus, we avoid regression techniques in favor of an analysis of variance approach.

[14] We required hospitals to have at least 25 inpatient days for each patient group, and at least 25 total outpatient visits. As a check, we implemented several variations on these minimum criteria (from as low as 10 to approximately 50) and found very few changes in the resulting data set.

DOH also classifies firms into peer-groups based on the size of the facility; 33 firms are small, rural hospitals, 28 are mid-sized, (primarily) urban hospitals, and 19 are large, urban hospitals.

Table 1 lists the variables used in the analysis. Efficiency was measured using seven outputs – total outpatient visits, and Medicare inpatient days, Medicaid inpatient days, all other inpatient days and casemix indices for each of our three inpatient groups.[15] Inputs included licensed hospital beds, the number of square feet in the hospital, and paid labor hours. The real price of supplies was used as an instrument for the price of a licensed bed, and was calculated as supply expenses divided by the number of licensed beds and the producer price index. Similarly, the real price of capital was calculated as the sum of interest and depreciation expenses divided by the square footage of the hospital and the producer price index. Lastly, the average real wage paid by the hospital served as a price for labor, and was measured as the sum of payroll and benefit expenses divided by the number of paid hours and the producer price index.[16]

Tables 2 through 6 provide statistics for the entire sample as well as disaggregating the data in several ways. Perhaps the most striking information in Table 2 is how much larger the mean outputs are than the medians – approximately twice as large. In addition, Medicare inpatients have a much larger casemix value than Medicaid or other inpatients. Other interesting values from Table 2 are the efficiency variables. In the total sample, the average technical efficiency was 0.88, with an average allocative efficiency of 0.92 and an average cost efficiency of 0.81. The average scale efficiency for the total sample was 0.91.

[15] Unfortunately, while we have quarterly data on all other outputs, our casemix data is measured annually. However, since annual casemix data will likely bias the results against a finding of seasonal inefficiency (and since our approach is to use an input oriented technique, which adjusts inputs holding outputs constant), this should not affect the reliability of our results, particularly if evidence of seasonal inefficiency is found.

[16] All input prices vary by quarter, as does the number of paid hours. Not surprisingly, the number of licensed beds and hospital square footage exhibit no quarterly variation.

More interesting information is found in tables 3 through 6, which disaggregate the data by quarter, by year, by peer group and by operating status. Looking at Table 3, there is no over-arching pattern in utilization. That is, there is no quarter that consistently has a higher mean number of patients in all categories, nor is there any monotonic relationship in inputs or input prices. We also tested for seasonal variation across any input prices, or any ratio of two input prices and found no evidence of significant (quarterly) seasonality.[17] In terms of outputs and inputs, no perceivable patterns were apparent when the data were disaggregated by year, as shown in Table 4.

As would be expected (Table 5) small rural hospitals had lower outputs and inputs than mid-sized, urban hospitals and large, urban hospitals. Input prices and casemix values followed the same pattern. Large, urban hospitals showed the highest average cost, allocative and technical efficiencies, but the lowest average scale efficiencies.

Table 6 disaggregates the data by profit status – for-profit hospitals, private nonprofit hospitals, and government hospitals. Government hospitals were the smallest, on average, in both workload and inputs, and paid the lowest input prices. The casemix indices of government hospitals were also lowest. For-profit hospitals were, on average, smaller in terms of output and inputs when compared to private nonprofit hospitals, and paid lower average wages but incurred higher average capital costs. The average casemix index for Medicare patients was lower, but higher for Medicaid patients and others. For-profit hospitals demonstrated higher average cost, allocative and technical efficiencies than private nonprofit or government hospitals, but lower scale efficiencies.

[17] Tests were conducted using both parametric (one-way ANOVA) and non-parametric tests (Kruskal-Wallis test) for the mean. The sign test was also used to test these same hypotheses at the median. Among all of these tests, the lowest probability value obtained was 0.239, with most probability values ranging between 0.5 and 0.9. Further details of these tests are available from the authors upon request.

Results of the Empirical Analysis

Table 7 summarizes the results of the Kruskal-Wallis test on the sample means, and the nonparametric Sign test on the sample medians.[18] The results of the test on the primary hypothesis – differences by quarter, are shown in the first two rows of the table. Using the Kruskal-Wallis test we reject the null hypothesis that the means of technical and cost efficiency are the same across quarters in favor of the alternative hypothesis that they differ. We do not find such evidence for allocative efficiency. For the medians (using the Sign test), we also find evidence to reject the null hypothesis of no difference (at the10 percent significance level) for allocative and cost efficiency. There is no evidence to support rejecting the null hypothesis that scale efficiency differs by quarter for means or medians. Examining the descriptive statistics in Table 3, we find that quarter one exhibits the highest mean and median levels of technical, allocative and cost efficiency. Quarter two's mean and median efficiency scores (for all three types of efficiency) are next highest, followed by quarters three and four. Thus, quarter one appears to be the "anchor" quarter.

Looking at the tests for mean and median differences by year, we find no evidence of technical or cost differences, but some evidence of differences in allocative inefficiency. Specifically, hospitals in 2001 showed significantly less allocative efficiency than in previous years (see Table 4). Combined with the findings when grouped by quarter, we conclude that aggregating efficiency measures to an annual analysis may miss some seasonal inefficiency, supporting our principal hypothesis.

As Table 7 shows, decomposing efficiency measures by peer group and operating status reveals distinct differences between the groups. In the case of the Sign test on technical

[18] Full results are available from the corresponding author.

efficiency by operating status, there are differences in mean or median efficiency between the groups. Thus, combining this information with the statistics in Tables 5 and 6, we conclude that for-profit firms and the large peer-group firms are much more efficient in terms of technical efficiency, allocative efficiency and cost efficiency, but much less efficient in scale efficiency. The last three groupings in Table 7 disaggregate by quarter and year, peer group and operating status, respectively. These results are consistent with those found for the individual analyses of year, peer group and operating status.

We find significant differences in allocative efficiency and scale efficiency only when we decompose the efficiency scores by year, or by quarter and some other factor such as peer group or operating status taken jointly. Indications are, then, that these results are primarily driven by the other jointly considered factor. That is, it is very likely that different firms address scale and allocative inefficiency in different ways, possibly using different quarters or seasons as their benchmark or anchor[19]. We are able to show that these findings may be consistent with seasonal efficiency, but that it becomes apparent only when the data are looked at more closely.

[19] Full results are available for the corresponding author.

Conclusions and Implications

Our main focus is, of course, on quarterly measures of efficiency. When we disaggregate by quarter we find seasonal differences in technical efficiency and cost efficiency (presumably driven by the seasonality in technical efficiency). The greatest mean technical efficiency is in quarter 1, followed by quarters 2, 4 and 3. Perhaps more interestingly is in the differences in mean technical efficiency as we move down the ranking. Quarter 1 shows a mean efficiency of 0.90, with a drop of 0.02 to a mean efficiency in quarter 2 of 0.88, followed by quarter 4 at 0.87 and quarter 3 at 0.86. Thus, the most likely scenario is that quarter 1 is the anchor quarter. Hospitals move away from the output normally encountered during quarter 1, breeding seasonal inefficiency. This last conclusion is reinforced by looking at median rather than mean technical efficiency by quarter. Quarter 1 again has the highest value, with 0.94, and second place is again quarter 2, but the median efficiency falls to 0.91. Quarters 3 and 4 both have median efficiency of 0.90.

Our main findings are thus twofold. First, seasonal efficiency is important, especially because we find that technical efficiency, the most commonly studied form of efficiency in analyses of health care institutions, does vary predictably by season. Secondly, by using data broken down by profit status or size as well as season, we find that allocative efficiency is also seasonal. Thus, how one aggregates or analyzes quarterly data (or by using yearly data) can provide very misleading results, primarily due to the seasonality inherent in efficiency measurement.

While our results are interesting, we intend them only as a first step, and emphasize that they should be viewed with caution. One limitation is the fact that our casemix variables are measured annually. Future studies that utilize casemix outputs (or casemix adjusted outputs) of shorter frequency will undoubtedly provide additional insights into the causes of seasonal inefficiency. Additionally, the use of square footage and licensed beds as capital and supply inputs may also be problematic, since these variables also do not change dramatically over the course of a year (or years). Other studies using different measures of capital and supplies may obtain different results. Finally, our sample consists of Washington state acute care hospitals. Other types of health care providers (long-term care facilities, outpatient clinics, etc.), or hospitals that serve a noticeably different socio-economic population may also exhibit different levels of seasonal inefficiency.

Figure 1: A Graphical Description of Seasonal Production and Inefficiency

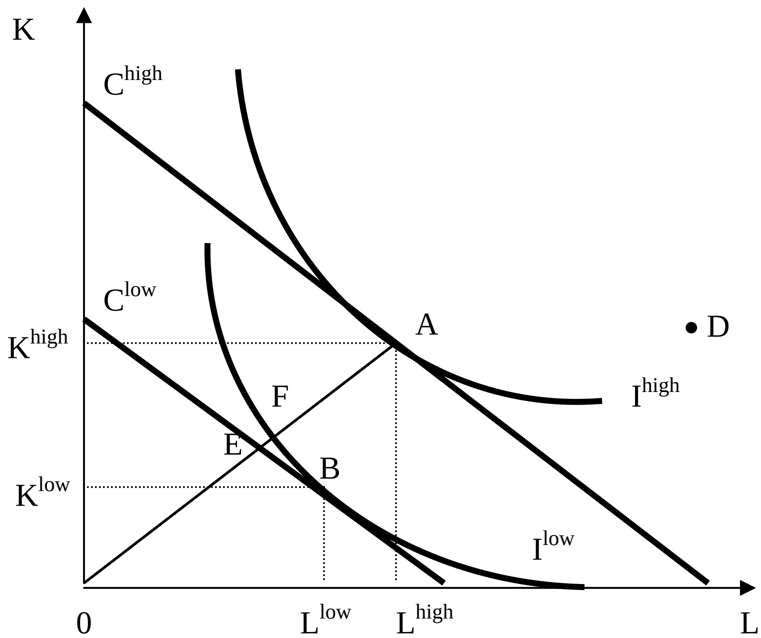

Figure 2: A Graphical Description of Seasonal Input Price Fluctuation and Inefficiency

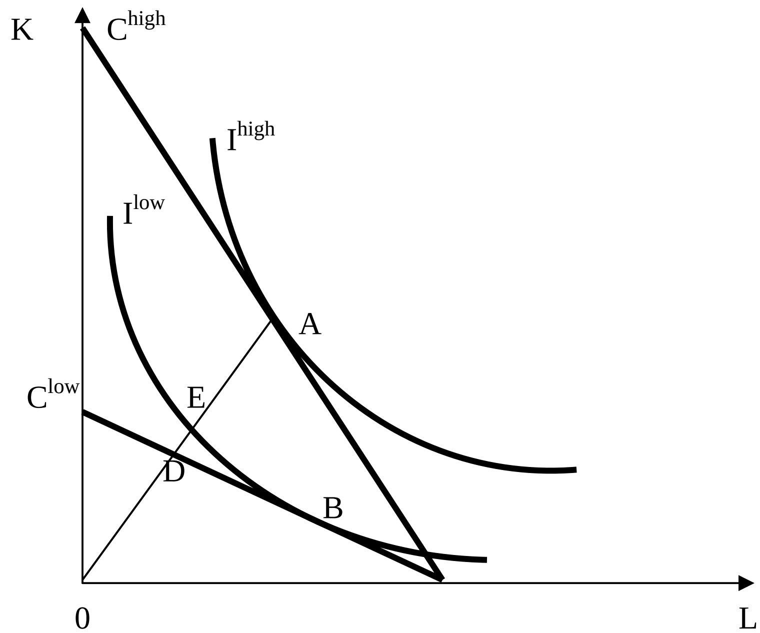

Figure 3: A Graphical Depiction of Seasonal Scale Inefficiency

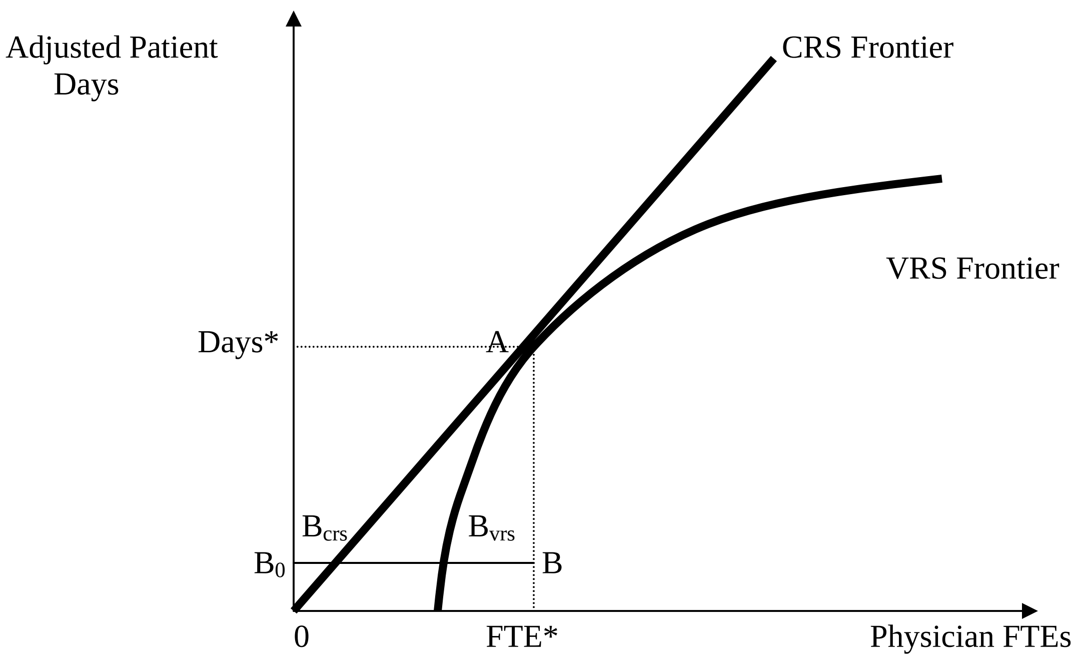

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Table 1: Variable Names and Definitions

Variable	Definition
Output and Casemix Variables	
TOPVIS	Total Outpatient Visits
CAREDAY	Medicare Inpatient Days
CAIDDAY	Medicaid Inpatient Days
OTHDAY	Non-Medicare, Non-Medicaid Inpatient Days
CARECMI	Medicare Casemix Index
CAIDCMI	Medicaid Casemix Index
OTHCMI	Non-Medicare, Non-Medicaid Casemix Index
Input Variables	
BEDS	Number of Beds in a Hospital
SQFEET	Square Footage of a Hospital
PAIDHOURS	Number of Paid Hours per Hospital
Input Prices	
PSUPP	Real Price of Supplies
PCAP	Real Price of Capital
PLABOR	Real Price of Labor
Efficiency Variables	
TE	Variable Returns to Scale Technical Efficiency Score
AE	Allocative Efficiency Score
CE	Cost Efficiency Score
SCALE	Scale Efficiency Score

Table 2: Descriptive Statistics (all firms, all years)

Variable	**Mean**	**Std. Dev**	**Minimum**	**1st Quartile**	**Median**	**3rd Quartile**	**Maximum**
Output and Casemix Variables							
TOPVIS	27211.80	38603.69	445.00	6015.50	13873.00	35100.00	274592.00
CAREDAY	2918.83	3296.72	40.00	421.25	1216.00	4925.25	17330.00
CAIDDAY	1631.24	2047.51	26.00	278.00	959.00	2237.00	14173.00
OTHDAY	2948.78	3734.33	26.00	490.00	1418.00	4047.75	24533.00
CARECMI	1.11	0.28	0.62	0.87	1.10	1.25	2.34
CAIDCMI	0.66	0.23	0.33	0.51	0.60	0.77	1.59
OTHCMI	0.81	0.26	0.42	0.64	0.76	0.90	1.87
Input Variables							
BEDS	166.65	159.86	15.00	48.00	106.00	253.00	860.00
SQFEET	224399.97	310587.90	13160.00	44001.00	113185.00	295400.75	3746813.00
PAIDHOURS	414428.74	487884.45	21429.00	76982.25	214399.50	627343.25	2205669.00
Input Prices							
PSUPP	12970.81	8987.31	133.47	5228.64	11889.34	17525.44	51513.29
PCAP	5.39	2.64	0.08	3.55	4.99	6.56	15.82
PLABOR	20.11	3.13	9.00	18.25	20.57	22.02	29.23
Efficiency Variables							
TE	0.88	0.12	0.39	0.79	0.91	1.00	1.00
AE	0.92	0.09	0.55	0.89	0.96	0.99	1.00
CE	0.81	0.15	0.37	0.70	0.82	0.95	1.00
SCALE	0.91	0.09	0.44	0.85	0.94	0.99	1.00

Table 3: Descriptive Statistics (by quarter)

	Quarter 1			Quarter 2			Quarter 3			Quarter 4		
Variable	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
Output and Casemix Variables												
TOPVIS	26004.87	13586.00	36702.55	26833.18	13788.00	38964.35	27737.73	14129.00	38118.72	28256.24	13635.00	40691.74
CAREDAY	3021.80	1271.00	3385.24	2816.76	1024.00	3240.59	2864.13	1203.00	3191.38	2976.16	1333.00	3383.44
CAIDDAY	1698.48	976.00	2089.71	1583.25	883.00	2037.66	1629.71	945.00	2035.07	1614.76	1050.00	2037.61
OTHDAY	2973.88	1484.00	3641.52	2830.78	1293.00	3739.34	2991.15	1419.00	3794.92	3000.32	1427.00	3776.01
CARECMI	1.11	1.09	0.28	1.11	1.09	0.28	1.12	1.10	0.28	1.11	1.10	0.28
CAIDCMI	0.66	0.60	0.23	0.65	0.59	0.23	0.66	0.60	0.23	0.66	0.60	0.23
OTHCMI	0.81	0.76	0.26	0.81	0.75	0.26	0.82	0.76	0.26	0.81	0.75	0.27
Input Variables												
BEDS	165.79	99.00	158.52	161.21	95.00	155.52	169.85	110.00	163.56	169.77	110.00	162.43
SQFEET	223287.20	113185.00	311444.35	217612.78	111742.00	308327.39	228073.02	114803.00	311116.78	228637.69	113455.00	313094.07
PAIDHOURS	400800.10	211474.00	467509.91	397873.76	196574.00	479849.52	426939.98	221547.00	500509.39	431965.91	218273.00	504216.48
Input Prices												
PSUPP	12673.42	12067.32	8543.59	12850.72	11887.78	8956.17	12956.10	11653.32	8978.81	13402.88	12036.46	9478.19
PCAP	5.28	4.93	2.63	5.34	4.91	2.63	5.47	5.03	2.66	5.47	5.10	2.67
PLABOR	20.20	20.80	3.10	20.20	20.58	3.20	19.91	20.38	3.04	20.14	20.64	3.19
Efficiency Variables												
TE	0.90	0.94	0.12	0.88	0.91	0.12	0.86	0.90	0.12	0.87	0.90	0.12
AE	0.93	0.96	0.09	0.93	0.96	0.09	0.92	0.95	0.09	0.92	0.95	0.09
CE	0.83	0.85	0.15	0.82	0.83	0.15	0.80	0.80	0.15	0.80	0.82	0.15
SCALE	0.91	0.94	0.09	0.91	0.94	0.09	0.91	0.94	0.09	0.91	0.94	0.10

Table 4: Descriptive Statistics (by year)

	1998			1999			2000			2001		
Variable	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**	**Mean**	**Median**	**Std. Dev.**
Output and Casemix Variables												
TOPVIS	24575.38	13391.00	36662.44	25221.30	13641.00	38090.50	31222.06	14441.50	47189.16	26794.67	13968.50	28520.89
CAREDAY	2645.99	1048.00	2951.31	2760.87	1053.00	3214.24	3088.31	1287.00	3483.13	3112.67	1679.00	3441.45
CAIDDAY	1505.07	867.00	1983.84	1544.18	816.00	2022.78	1619.13	1000.00	1985.81	1834.99	1187.00	2185.96
OTHDAY	2790.03	1411.00	3516.54	2860.80	1345.00	3833.80	2972.83	1449.00	3631.20	3142.53	1540.50	3963.81
CARECMI	1.12	1.12	0.28	1.11	1.10	0.26	1.12	1.10	0.31	1.09	1.07	0.28
CAIDCMI	0.67	0.60	0.22	0.66	0.60	0.23	0.67	0.60	0.25	0.63	0.58	0.21
OTHCMI	0.81	0.75	0.26	0.80	0.75	0.25	0.83	0.77	0.28	0.81	0.75	0.25
Input Variables												
BEDS	159.49	95.00	148.74	162.43	86.00	165.94	170.56	110.00	161.61	172.42	119.00	163.04
SQFEET	182853.90	91801.00	191985.40	188386.61	91801.00	212249.62	231448.81	120174.50	238319.44	285219.26	137330.00	484087.63
PAIDHOURS	383833.44	198280.00	454784.20	394270.03	196574.00	481892.08	438343.97	215906.00	521610.72	432679.59	232830.50	483374.97
Input Prices												
PSUPP	11663.30	10923.52	8240.75	12495.16	11802.62	8565.13	13724.42	12818.50	9801.75	13728.45	12577.98	8915.21
PCAP	5.58	5.15	2.73	5.83	5.33	2.79	5.29	4.87	2.60	4.95	4.62	2.42
PLABOR	19.55	19.96	2.94	19.91	20.37	2.91	20.48	20.81	3.11	20.39	21.04	3.42
Efficiency Variables												
TE	0.87	0.90	0.12	0.88	0.93	0.12	0.88	0.91	0.12	0.87	0.90	0.12
AE	0.94	0.96	0.08	0.93	0.96	0.08	0.92	0.96	0.09	0.91	0.94	0.10
CE	0.82	0.83	0.14	0.82	0.83	0.14	0.81	0.82	0.15	0.80	0.82	0.16
SCALE	0.90	0.93	0.10	0.90	0.93	0.10	0.92	0.94	0.09	0.92	0.94	0.08

Table 5: Descriptive Statistics (by peer group)

Variable	Mean	Small, Rural Hospitals Median	Std. Dev.	Mean	Mid-Sized, Urban Hospitals Median	Std. Dev.	Mean	Large, Urban Hospitals Median	Std. Dev.
Output and Casemix Variables									
TOPVIS	7889.41	4902.00	8056.44	22332.61	17960.00	17086.10	66653.03	49715.00	59364.42
CAREDAY	652.91	426.00	785.66	2728.14	2590.50	2045.81	6942.66	6214.00	3686.78
CAIDDAY	1073.27	348.00	1333.10	983.59	822.00	762.47	3569.04	2695.00	2992.20
OTHDAY	684.68	467.00	610.18	2249.95	1921.50	1795.66	7770.69	7956.00	4554.74
CARECMI	0.89	0.85	0.13	1.12	1.14	0.15	1.47	1.48	0.25
CAIDCMI	0.56	0.51	0.16	0.61	0.60	0.14	0.89	0.82	0.28
OTHCMI	0.66	0.64	0.12	0.78	0.80	0.12	1.11	1.05	0.33
Input Variables									
BEDS	56.73	48.00	34.81	152.83	132.00	103.43	369.07	340.00	167.04
SQFEET	57518.72	39851.00	44292.93	185749.98	137330.00	151326.35	559539.35	520565.00	455872.85
PAIDHOURS	90514.06	71071.00	66575.95	327910.17	243187.50	241920.95	1083059.02	911655.00	523424.33
Input Prices									
PSUPP	7010.20	4766.55	5419.43	12908.06	12288.64	5666.33	22863.82	20379.58	9271.15
PCAP	3.92	3.72	1.79	5.88	5.21	2.65	7.03	6.42	2.57
PLABOR	17.95	18.08	3.00	20.98	21.07	2.13	22.31	21.94	2.39
Efficiency Variables									
TE	0.87	0.92	0.14	0.86	0.88	0.12	0.92	0.95	0.09
AE	0.90	0.94	0.11	0.92	0.95	0.08	0.96	0.98	0.05
CE	0.79	0.78	0.17	0.79	0.80	0.13	0.89	0.93	0.11
SCALE	0.93	0.98	0.09	0.90	0.93	0.08	0.88	0.90	0.09

Table 6: Descriptive Statistics (by operating status)

Variable	Mean	For-Profit Hospitals Median	Std. Dev.	Mean	Private, Nonprofit Hospitals Median	Std. Dev.	Mean	Government Hospitals Median	Std. Dev.
Output and Casemix Variables									
TOPVIS	27424.39	19877.00	17400.01	38981.27	24061.00	48579.72	16071.35	7399.00	23578.79
CAREDAY	2612.74	2592.00	1588.90	4703.72	4384.00	3726.76	1268.87	483.00	1807.08
CAIDDAY	686.00	565.00	407.61	1988.63	1395.00	1721.58	1404.15	436.00	2356.90
OTHDAY	1413.57	1648.00	734.77	4549.40	3029.00	4344.96	1616.49	719.50	2530.83
CARECMI	1.20	1.26	0.20	1.25	1.20	0.27	0.97	0.92	0.23
CAIDCMI	0.76	0.84	0.15	0.71	0.64	0.22	0.59	0.53	0.22
OTHCMI	0.90	0.89	0.23	0.89	0.85	0.22	0.73	0.66	0.28
Input Variables									
BEDS	138.30	149.00	55.59	251.16	225.00	176.92	90.15	50.00	100.49
SQFEET	145591.02	137330.00	64740.36	341800.85	249361.00	386219.33	122730.84	56466.00	183217.62
PAIDHOURS	256103.84	230746.00	138617.28	621595.98	497535.00	519980.79	237272.37	83344.50	398252.67
Input Prices									
PSUPP	11452.92	11813.48	3868.23	15780.96	14588.77	8350.30	10494.14	7032.52	9230.50
PCAP	7.53	7.60	3.41	6.15	5.38	2.37	4.42	3.89	2.40
PLABOR	19.80	19.58	1.60	21.30	21.30	2.49	19.03	19.23	3.40
Efficiency Variables									
TE	0.92	0.93	0.07	0.88	0.90	0.11	0.87	0.91	0.13
AE	0.98	0.98	0.02	0.95	0.97	0.06	0.90	0.94	0.11
CE	0.90	0.91	0.08	0.84	0.85	0.13	0.78	0.77	0.16
SCALE	0.86	0.86	0.06	0.90	0.93	0.09	0.93	0.97	0.09

Table 7: Results of the Hypothesis Tests

Grouping	Test	TE	AE	CE	Scale	df
Quarter	K-W	**12.167**	4.618	**11.357**	1.128	3
	Sign	*7.847*	6.392*	6.166*	1.235	3
Year	K-W	1.963	*8.641*	3.571	6.575*	3
	Sign	2.963	*10.440*	1.901	2.932	3
Peer Group	K-W	**53.048**	**83.083**	**95.168**	**93.018**	2
	Sign	**57.464**	**70.657**	**83.259**	**76.284**	2
Operating Status	K-W	*6.559*	**64.765**	**54.222**	**79.159**	2
	Sign	3.999	**48.155**	**50.408**	**75.744**	2
Quarter & Year	K-W	15.609	16.431	16.957	8.843	15
	Sign	12.827	20.276	11.332	6.938	15
Quarter & Peer Group	K-W	**67.826**	**91.490**	**109.126**	**94.782**	11
	Sign	**68.566**	**79.987**	**91.544**	**79.576**	11
Quarter & Operating Status	K-W	*21.579*	**70.284**	**67.249**	**80.772**	11
	Sign	14.941	**55.763**	**57.823**	**77.139**	11

Bold indicates reject H0: no difference in means at $\alpha \leq 0.01$
Italic indicates reject H0: no difference in means at $\alpha \leq 0.05$
* indicates reject H0: no difference in means at $\alpha \leq 0.10$