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The impact of TennCare on hospital efficiency

Chang · Troyer

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The impact of TennCare on hospital efficiency

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Abstract This study measures the effect of TennCare, a Medicaid managed care reform initiated in 1994, on the efficiency of hospitals in Tennessee. We apply a multiple-output stochastic frontier approach to a panel dataset that represents all short-term acute care hospitals operating in Tennessee for 1990–2001 and find a modest gain in operating efficiency overall. Our results also reveal that the effect of reform on hospital efficiency varies significantly with the admitting hospital's TennCare patient load and whether the hospital is located in an urban or rural area. During the study period, high-TennCare hospitals in urban areas saw efficiency gains in the 4 years immediately after the implementation of the program while high-TennCare hospitals in rural areas had significant efficiency losses. The effects immediately following the program's implementation on low-TennCare urban and rural hospitals are similar to those experienced by hospitals with high-TennCare admissions but the magnitude of the effects are much smaller. Policymakers considering large scale reforms of this type should be careful to take into consideration the likely differential responses from urban and rural hospitals that are prone to differ in payer mix and capacity to improve efficiency.

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1 Introduction

On January 1, 1994, Tennessee implemented a bold Medicaid managed care reform called TennCare [1, 2]. Studies have examined TennCare's effects on a variety of outcome measures including access and quality of care [3–6], a mental health care carve-out program [7], consumer satisfaction with care [8], and the financial future of the program [9–11]. To date, however, the literature is silent on TennCare's impact on hospital efficiency. The objective of this study is to explore the effect of TennCare on the efficiency of short-term acute care hospitals operating in Tennessee.

The original overriding objective of TennCare was to expand health coverage beyond the Medicaid population to include the previously uninsured and uninsurable individuals while slowing down the uncontrollable growth of the Medicaid budget. Structurally, the state converted its traditional, centrally controlled, fee-for-service Medicaid program into a capitated managed care program that emphasized a variety of managed care practices such as capitation, selected contracting, and utilization review to improve efficiency and quality of care [12]. A decade later, TennCare encountered major financial difficulties and made painful decisions to cut back enrollment and benefits. During the period under study (1990–2001), however, TennCare consistently maintained coverage of three major population groups that included the Medicaid-eligible, uninsured individuals who had been rejected by an insurance company, and children whose individual family incomes were below 200% of the federal poverty level. During the same period, TennCare services were offered through contracted managed care organizations that arranged for service delivery and paid their respective networks of providers under a negotiated fee-for-service arrangement.

Several key facts point to the financial pressure placed on Tennessee hospitals by TennCare that might have impacted the cost efficiency of hospitals. TennCare dramatically increased Medicaid enrollment in Tennessee from the original 800,000 to 1.3 million while trying to improve quality through managed care practices [1, 9]. The pledge by TennCare to federal authorities to slow down the growth of the budget while delivering care to more people also resulted in paying providers a lower reimbursement rate per patient. A study sponsored by the Tennessee Hospital Association found that Medicaid reimbursed 98.1% of hospital costs in 1993 before TennCare and that the reimbursement level had declined to about 60% by 1999 [13, 14]. Between 1993 and 2000, occupancy rates in Tennessee hospitals fell from 47.2% to 42.2%, and the average length of stay fell from 6.1 days to 5.0 days [15]. In addition, there was a reduction in care disbursed to Medicaid patients in safety net hospitals and an increase in care disbursed to TennCare patients in non-safety net hospitals [12].[1] Given the dual financial pressures caused by TennCare and the Balanced Budget Act of 1997, questions remain regarding how hospitals in Tennessee have responded to the reductions in reimbursement and a sudden expansion of public-sector managed care.

In response to financial pressures, a hospital can in the long run diversify its activity [16], change ownership status from, for example, nonprofit to for-profit [17, 18], or close down and leave the market altogether. In the short run, a financially stressed hospital can cut operating expenses and quality of care [19–21], reduce indigent care, and chose a more profitable mix of third-party payers [22, 23]. However, previous researchers have paid insufficient attention to the question of whether hospitals react to financial pressures brought on by a sudden conversion from fee-for-service Medicaid to privatized managed care by increasing the operating efficiency with which services are delivered. Though not a primary impetus of the TennCare experiment, changes in hospital operating efficiency and the variations of this change across hospitals of different types and locations can contribute to the understanding of the potential impact of state-level health reform.

To measure the effect of TennCare on the efficiency of hospitals in Tennessee, we apply a multiple-output stochastic frontier approach to a panel data set that represents all short-term acute care hospitals operating in Tennessee for 1990–2001. The data are based on a state-mandated annual survey of hospitals called the Tennessee Joint Annual Report of Hospitals. The long period covered by the data permits a thorough examination of cost efficiency prior to TennCare's implementation (1990–1993), during the initial years of TennCare (1994–1997), and in subsequent years (1998–2001). More recent data are available but their use make the results difficult to interpret because TennCare in the post 2001 period changed its financial arrangement with managed care organizations from a capitation-based risk contract to an administrative service organization (ASO) contract that shifted the financial risk to the State.

Two groups of variables will be used to examine cost efficiency: (1) traditional measures of production costs including quantity of output and input prices, and (2) explanatory variables thought to influence hospital operating efficiency, including the proportion of TennCare patients, the proportion of Medicare patients, binary variables that capture policy changes over time, and other factors under the control of hospital management that are likely to effect efficiency. Our longitudinal examination of hospital level data permits the determination of the extent to which TennCare as a key state-level managed care experiment has affected hospital efficiency. In addition, we will explore the differences in the impacts of TennCare on Tennessee hospitals with different characteristics and located in different areas of the state.

2 Literature review

Economists have long understood that hospitals are multiproduct firms that do not use best-practice combinations of inputs [24–26]. Studies of hospital inefficiency have found that the mean hospital inefficiency typically falls in the 12–15% range [26–29] and that over time during the 1990s, the level of inefficiency gradually declined in response to the growth of managed care and other market forces that had exerted pressures on hospitals to improve operational performance [30, 31].

Previous studies of hospital inefficiency have also examined the effects of external changes in market and regulatory environments such as the implementation of the prospective payment system (PPS) in 1983 [26, 32], the growth and penetration of managed care [30, 33], and government budget and health care reforms [34, 35]. In response to the growing concern over health care quality in the late 1990s and early 2000s, many researchers have also focused on the effects of financial pressure placed on hospitals as a result of PPS payments and penetration of HMOs in local hospital markets on both the level of technical efficiency and quality of care in hospitals [35, 36].

[1] Safety net hospitals provide a significant level of care to low-income and uninsured individuals.

Empirical investigations of hospital inefficiency have typically used one of two approaches—data envelopment analysis (DEA) or the stochastic frontier approach (SFA).[2] DEA is a non-parametric, linear programming approach for measuring relative efficiency for a group of operating units where the relative values of variables are unknown [37, 38]. It does not require assumptions about the statistical properties of the variables and can accommodate multiple inputs and outputs [39]. It has been used in health care [40, 41] and can answer questions such as by how much can costs be reduced without changing the quantities of hospital outputs such as inpatient days or hospital admissions.

SFA, developed by Aigner et al. [43] and Meeusen and van den Broeck [44], is an econometric approach that uses regression to estimate a cost function of a particular form. It assumes that departures from the best-practice combination of inputs by a hospital may be stochastic (due to factors over which the hospital has no control) or deterministic (due to choices made by the hospital that lead to inefficiency). In recent years, at least a dozen refereed articles have used the SFA approach to estimate hospital inefficiencies in the USA with ten of these reviewed in Hollingsworth [42]. Some of them focused on the relative inefficiencies among different hospitals according to ownership [29, 45], teaching status [29], and the size of hospitals [46, 47]. Others have examined the impact of specific policy changes. For example, Mobley [48] examined the effects of the 1982 California Medicaid Reform Act that increased competition and awarded contracts to hospitals that took measures to improve efficiency, leading to efficiency gains post reform.

Economists have criticized DEA because it does not explicitly distinguish between random variations in productivity and variations in technical efficiency [49]. They favor SFA for another reason—it provides estimates of X-inefficiency which are defined as the difference between optimal performance and actual performance [30, 50]. Another advantage of SFA is that it is grounded firmly in the theory of the firm, relying strongly on theory to guide selection of explanatory variables and functional form. In contrast, DEA requires fewer restrictive assumptions and is much more flexible. However, the location of the DEA-derived frontier may be more sensitive to outliers that result in inappropriate positioning of the frontier. In addition, SFA allows for the possibility of measurement error in the data something that is a distinct possibility in the context of hospital reporting. Finally, DEA relies on peers with a comparable mix of outputs to generate efficiency scores, which results in a more selective use of data than the SFA approach.

SFA is not without detractors. For instance, Newhouse [49] argues that specification problems, such as the way that hospital outputs and quality are measured with imprecision or left out of the specification entirely, may have a more severe effect on SFA estimates than estimates derived from OLS. The strong assumptions about functional form and related concerns about multicollinearity and heteroskedasticity are probably the biggest drawbacks of SFA relative to DEA.[3] Despite these concerns, in this study, we use the SFA approach and estimate cost functions using a panel dataset from Tennessee for the period of 1990–2001.

Recently, Baccouche and Kouki [52] examined the sensitivity of SFA cost efficiency estimates to the choice of the distribution of the inefficiency error term when using a panel of firms.[4] They found that the generalized half-normal and truncated normal provide more reliable inefficiency estimates than the exponential and the half normal. In addition, Rosko and Mutter [53] in an excellent review of SFA cost efficiency for hospitals find that the cost inefficiency estimates are quite robust to changes in the distributional assumption. We use the truncated normal, which is a special case of the half normal, in our empirical model.

3 Models, data and estimation issues

3.1 Empirical approach

Researchers using the stochastic frontier approach for investigating hospital efficiency have used either a single-step or a two-step procedure. Several authors [26, 29, 54, 55] have considered predictors of hospital inefficiency using a two-step procedure: (1) estimation of a stochastic frontier function and computation of predicted inefficiency for each facility in each period, and (2) use of the computed level of inefficiency as the dependent variable in an exploration of factors that influence inefficiency. This two-step procedure is problematic because the computed inefficiency effects are, by assumption, independently and identically distributed. In the second step, however, the inefficiencies are modeled as a function of firm-specific factors, implying that they are not identically distributed if the coefficients on the factors are statistically significant [56].

[2] This review benefits from an excellent review article by Hollingsworth [42].

[3] For a detailed discussion of the strengths and weaknesses of SFA and DEA techniques for modeling efficiency of health care firms, see Jacobs et al. [51].

[4] The Baccouche and Kouki paper studies Tunisian manufacturing firms, not hospitals.

We prefer the single-step model developed by Battese and Coelli [57] that allows for the estimation of a stochastic frontier cost function in which inefficiency effects for each hospital in each year are explicitly modeled as a function of a vector of firm-specific variables and a random error. This single-stage estimation approach has another advantage in that it can accommodate unbalanced panel data that are common for industries that experience frequent entries and exits of firms.

$$C_{it} = x_{it}\beta + (v_{it} + u_{it}) \tag{1}$$

where

- C_{it} the logarithm of total costs of the ith firm in the tth period;
- x_{it} a $k\times 1$ vector of log transformed outputs, input prices, and other factors that influence the level of costs for the ith firm in the tth period,
- β a vector of parameters, with observations indexed by both hospital, $i=1, 2,\ldots,n$, and time, $t=1, 2,\ldots,T$,
- v_{it} statistical noise assumed to be distributed as $N(0,{\sigma_v}^2)$, and independent of u_{it}, the efficiency effects, and
- u_{it} non-negative random variables obtained by truncation (at zero) of the normal distribution with mean $z_{it}\delta$ and variance σ^2,

where z_{it} is a vector of variables (including an intercept term) which may directly influence the inefficiency of the ith hospital in the tth year; and δ is an vector of parameters to be estimated. Given the definition of u_{it} from above, the inefficiency effects may be written as:

$$u_{it} = z_{it}\delta + w_{it}. \tag{2}$$

The values of the unknown parameters in 1 and 2 are obtained simultaneously using the method of maximum likelihood, where the single log likelihood function being estimated includes elements from both 1 and 2.

The panel approach by Battese and Coelli [57] allows for time-varying inefficiency effects that can be modeled as a function of both time variant and time-invariant environmental factors. Both the fixed effects regression and generalized least squares (following Schmidt and Sickles [58]) have been used by other authors to estimate panel data cost efficiency models, but these methods have characteristics that make them less than ideal for our purposes. First, fixed effects models control for any firm-level heterogeneity that remains constant over time. In our model, this would certainly include geographic location and would likely include engagement in medical education. Given our focus on the policy implications of TennCare reform, we are interested in how these important characteristics differentially affect costs and inefficiency levels. This makes the fixed effects estimator less desirable in our case. Another potential panel estimation approach is generalized least squares. While this approach allows for the inclusion of time invariant regressors, the Schmidt and Sickles [58] approach does not allow one to model changes in inefficiency levels over time, which is the primary focus of our paper.

The level of cost efficiency of the ith hospital in the tth year may be calculated as the ratio of the frontier minimum cost, where u_{it}=0, to observed total costs for the hospital. The cost efficiency scores are computed net of factors, x_{it} in Eq. 1, that influence costs. Following Coelli et al. [56], cost efficiency is defined as:

$$\mathrm{CE}_{it} = \exp(u_{it}). \tag{3}$$

This measure ranges in value from one to infinity, where the most efficient (low cost) hospitals take a value of one. When estimating production functions, SFA efficiency estimates are generally reported with a value of one for the most efficient firms, and less efficient firms receive a value of less than 1. To express our results in a similar way, taking the inverse of CE_{it} allows a hospital with an efficiency of one to be on the frontier; hospitals with values for the inverse of CE_{it} of less than one are less cost efficient. One minus the inverse of CE_{it} results in an estimate of cost inefficiency, indicating the percentage distance from the efficient frontier. These inefficiency scores include the influence of the factors included in z_{it}.

Following the examples of typical of hospital efficiency analyses, we use an input–output approach to obtain the cost inefficiency measures. The cost function involves combining all inputs into a single measure (total costs) and considering the extent to which each hospital's costs exceed that predicted by the outputs produced (and other elements included as explanatory variables). In the examination of the efficiency of health care organizations, it is more common to see production costs than it is to see the production process (and firm outputs) modeled. Most hospitals produce multiple outputs and those outputs are difficult to quantify; outcome data are rare and counts of activities require complex risk adjustment and do not control for quality differences. Fortunately, the cost function under the cost-minimization assumption is the dual of the production function, providing equivalent results.

As part of our empirical approach, we conduct two specification tests. First, we examine whether there is support for an examination of the inefficiency effects. Second, we consider the appropriate functional form. We first use the estimate of $\gamma = \sigma_u^2/\sigma^2$where $\sigma^2 = \sigma_v^2 + \sigma_u^2$ to determine whether the two-equation modeling of the cost function (Eq. 1) and inefficiency effects (Eq. 2) is an improvement over modeling the cost function using OLS. We can jointly test the hypothesis that g equals 0 and that the coefficients on the inefficiency explanatory variables (d)

are jointly insignificant. If all d parameters and g are equal to 0, the model may be efficiently estimated using OLS [59]. The second hypothesis test conducted considers whether the Cobb–Douglas functional form is appropriate, where the comparison cost function is the translog. The Cobb–Douglas cost function is a more restrictive functional form than the translog, which places no restrictions upon returns to scale (which are constant for the Cobb–Douglas) or elasticities of substitution (which are equal to 1 in the Cobb–Douglas). The translog model involves the estimation of a large number of parameters on the squared and cross-product terms for input prices and outputs, which may create multicollinearity problems. We test the null hypothesis that the Cobb–Douglas functional form of the cost function is appropriate by testing that the second-order coefficients from the translog are jointly equal to 0. The outcomes of the specification tests are given in Section 4 below.

3.2 Data

Our primary source of data is the Tennessee Department of Health's Joint Annual Reports of Hospitals for the period 1990–2001. We restrict our analysis to short-term acute care hospitals defined as general-medical/surgical hospitals with a non-zero value for outpatient visits.[5] The number of hospitals in the sample varies over time, where new facilities open, some facilities close or merge with other facilities, and incomplete information from the Joint Annual Reports of Hospitals is provided for one or more of the variables of interest in some years. The SFA approach used in our analysis can accommodate an unbalanced panel [59]. The unit of observation for the analysis is a particular hospital in a given year.

We also use two additional sources of data: (1) the PPS payment impact file from the Centers for Medicare and Medicaid Systems, which contains the Medicare case-mix index, and (2) the area resource file. Due to a lack of data on patient flows, we define the market as the county, and use the area resource file for market-level measures included in the model, including population, income, and urban/rural location.[6]

[5] The restriction of the sample to firms with non-zero values for outpatient visits is necessitated by the choice of functional form, which requires the log transformation of all outputs and input prices. In addition, for hospitals to be directly comparable, the frontier must be defined based on a set of firms who produce a similar set of outputs using a similar set of inputs. Hospitals with zero levels of outpatient visits are likely to be producing a different product with a different set of inputs than hospitals that are producing both inpatient and outpatient care.

[6] Other authors have used the county as the market area for hospital care. See, for example, Friedman and Basu [60], Laditka et al. [61], Laditka and Laditka [62], and Laditka and Laditka [63].

3.3 Empirical model specification

Our modeling approach begins with the estimation of a homogeneity-constrained generalized translog cost function (Eq. 4) and inefficiency effects (Eq. 5) of the following form:

$$\begin{aligned}\ln\left(\frac{TC_{it}}{W_{it}}\right) = {} & \alpha_0 + \alpha_1 \ln\left(\frac{Y_{1it}}{W_{it}}\right) + \alpha_2 \ln\left(\frac{Y_{2it}}{W_{it}}\right) + \beta_1 \ln\left(\frac{P_{it}}{W_{it}}\right) \\ & + \phi_1\left[\ln\left(\frac{Y_{1it}}{W_{it}}\right)\right]^2 + \phi_2\left[\ln\left(\frac{Y_{2it}}{W_{it}}\right)\right]^2 \\ & + \phi_3\left[\ln\left(\frac{P_{it}}{W_{it}}\right)\right]^2 + \theta_1\left\{\left[\ln\left(\frac{Y_{1it}}{W_{it}}\right)\right]\left[\ln\left(\frac{Y_{2it}}{W_{it}}\right)\right]\right\} \\ & + \theta_2\left\{\left[\ln\left(\frac{Y_{1it}}{W_{it}}\right)\right]\left[\ln\left(\frac{P_{it}}{W_{it}}\right)\right]\right\} \\ & + \theta_2\left\{\left[\ln\left(\frac{Y_{2it}}{W_{it}}\right)\right]\left[\ln\left(\frac{P_{it}}{W_{it}}\right)\right]\right\} \\ & + \sum_{k=1}^{6} \tau_k X_{kit} + v_{it} + u_{it}\end{aligned} \tag{4}$$

$$u_{it} = \sum_{l=1}^{19} \delta_l Z_{it} + w_{it} \tag{5}$$

where the dependent variable in the cost function is the log of total costs (TC$_{it}$), normalized by the price of labor (W_{it}), Y_{1it} is inpatient admissions, and Y_{2it} is outpatient visits. The X_{kit} are variables, described below, that are thought to influence the level of costs for the ith firm in the tth period, v_{it} is the random component of the error term in the cost function, and the u_{it} represent cost inefficiency. The Z_{it} are posited to affect inefficiency levels. We discuss the construction of all of the key variables below.

3.4 Cost function measures

As noted by Jacobs et al. [51] (pp. 41–50), the issue of which explanatory variables to include in the specification of the cost function and inefficiency effects is not without controversy. They outline two schools of thought on the issue: cost functions should be derived from the theory of the firm vs. cost functions should be based on theories of regulation. Our work follows more closely the first approach, where we are analyzing costs from the perspective of the hospital using a neoclassical framework. As such, costs depend on outputs and input prices, where constraints that are unavoidable in the short run, such as status as a teaching hospital, are placed in the cost function.

We use total annual expenses reported by each of the hospitals to represent total hospital costs. Two outputs are used in the cost function estimation: outpatient visits and inpatient days. Two input prices are used: the price of labor (wages plus benefits per FTE reported), and the price of capital (depreciation plus interest expense per licensed bed). We scale both total costs and the price of capital by the

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price of labor. This normalization imposes the theoretical condition that the cost function is linearly homogeneous in input prices and essentially adjusts for inflation that is common to the data series. The final measures are log transformed prior to estimation.

Heterogeneity of hospital outputs such as inpatient days and outpatient visits is an important concern for researchers attempting to correctly identify the cost function and remaining inefficiency for hospitals. To adjust for differences in case complexity among patients admitted to a hospital, we multiply inpatient days by the Medicare case-mix index.[7] While the constructed index is based on Medicare patients, it is likely to be correlated with case-mix indices based on all hospital admissions [64]. For outpatient visits, we include a variable indicating the proportion of outpatient visits that are emergency room visits, allowing the cost function to differ for hospitals that vary on this dimension.

We include a set of variables to control for heterogeneity in costs across hospitals. The first of these is the mortality rate. This measure, which is unadjusted for mortality risk given data limitations, may not reflect the process of care [65] and may pick up unmeasured acuity differences across facilities that are not captured by adjusting inpatient days using the Medicare case-mix Index.[8] However, the mortality rate may also be associated with lower costs of patients in hospitals that are under-providing essential care. As such, it is difficult to form a hypothesis regarding the sign of the coefficient on mortality rate. Second, we include a binary variable indicating whether the hospital is affiliated with a medical school and another indicator of whether the hospital has received AMA approval for residencies. Hospitals affiliated with medical schools are likely to be more heavily engaged in medical education than hospitals who only offer residencies, where both endeavors may increase costs and be correlated with the case-mix of outputs.[9]

[7] We were only able to obtain Medicare case-mix data from 1993–2001. Given the lack of data, we assigned 1993 value for the Medicare case-mix Index for each hospital to the same hospital in 1990, 1991, and 1992. When considering the correlation between the Medicare case-mix Index and the Medicare case-mix Index lagged one period for 1993–2001, we find that the correlation is .95271 for our data. This suggests that there is little variation in this measure over time at the hospital level.

[8] The mortality rate is based on the number of deaths in the hospital divided by the number of admissions. Unfortunately, we only have the number of deaths for 1990–1999. So, for 2000 and 2001, we assign the 1999 value for the mortality rate to each hospital.

[9] In the data, we have an indicator for JCAHO accreditation, which has been used by prior researchers as a quality indicator. However, it is omitted because it is highly correlated with the indicator for medical school affiliation, and the vast majority of observations were for accredited hospitals. As will be discussed in the concluding section of this paper, the omission of a meaningful quality measure is a weakness of our paper.

Finally, we include two additional control variables in the cost function to account for differences in costs over geographic areas (counties): county population (in 10,000s) and mean per capita personal income in a county (in $10,000s). As discussed in the Section 4 later in this paper, we also consider the importance of urban vs. rural location in estimating the cost function.

3.5 Inefficiency measures

A second set of variables thought to influence hospital inefficiency is used in the estimation process. First, to allow for an examination of the year-to-year change in hospital inefficiency, we include a series of binary variables for each year, where 1993, the last year before TennCare was started, serves as the reference period. As noted in the introduction, Tennessee's program to cover the uninsured has been posited to place financial pressure on hospitals. Following Leibenstein's [68] theory of X-inefficiency, hospitals faced with cost pressure from TennCare may initially take no action initially. If pressure continues to increase to some threshold level, however, some hospitals would begin to adjust to the change by changing levels of efficiency. Therefore, we hypothesize that hospital inefficiency will decrease over time, albeit perhaps not in the period immediately after the implementation of TennCare.[10]

Hospital inefficiency levels are likely to vary with the fiscal pressures associated with government adjustments in reimbursements for TennCare/Medicaid and Medicare services. Hospitals serving a higher proportion of patients covered under the TennCare/Medicaid and Medicare programs would tend to operate more efficiently if the relatively low reimbursement rates for these programs cause firms to control costs, increasing efficiency levels. Following the suggestion of Menke [69], Robinson [70], and Connor et al. [71] that increasing the proportion of Medicare or TennCare/Medicaid patients has a negative effect on hospital costs, we hypothesize that serving a higher proportion of either payer type is associated with a decreased level of inefficiency.

To test the effects of Medicare and TennCare patient loads on inefficiency, the use of interaction terms between time indicators and the proportion of TennCare/Medicaid or Medicare patients may be appropriate in a linear modeling environment. However, our model is non-linear given the modeling of both the cost function and inefficiency effects. Ai and Norton [72] discuss how interaction terms in nonlinear models are

[10] To our knowledge, there were no other significant structural changes, such as changes in Certificate-of-Need laws in Tennessee, that could significantly affect hospitals over the period considered.

routinely misinterpreted, where, "the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term, can be of opposite sign, and its statistical significance is not calculated by standard software." To avoid the use of interaction terms, we stratify our sample based on the median proportion of inpatient admissions that were funded by TennCare/Medicaid in all years for each hospital. The median proportion of admissions that were for TennCare/Medicaid was 17.7% for the study period. Using this value, we divided the sample into hospitals with greater than the median TennCare/Medicaid admissions and hospitals with a proportion of TennCare/Medicaid admissions that is less than or equal to the median. We expect that hospitals in the sample with more TennCare/Medicaid admissions will be impacted more by the implementation of TennCare than hospitals with more patients with other payment sources.

When considering changes in hospital efficiency since TennCare, it is important to also examine other statewide or national policy changes that would have also impacted hospitals during the same period. If changes in inefficiency are attributable to TennCare reform, they should not coincide with other large scale reforms. To our knowledge, there were no other statewide policy changes during the period we studied. Turning to federal initiatives, it is important to note that during the study period Tennessee did not offer a separate State Children's Health Insurance Program (SCHIP) authorized by the Balanced Budget Act (BBA) of 1997 that could have potentially altered the demand for, and the costs of, hospital services. However, the BBA of 1997, which impacted hospital inpatient Medicare revenue beginning in 1998, may be responsible for some of the changes in hospital inefficiency from 1998–2001. We will reconsider this issue in our discussion of the results below.

Also included in the inefficiency model are the Herfindahl–Hirschman index (HHI) for the hospital's county location and the ownership type of the hospital. The HHI is constructed using the sum of the squared market shares for all hospitals in the county, where market shares are computed using the number of inpatient days for each hospital in the county. Firms in less concentrated areas may feel more pressure to control costs and decrease inefficiency [66]. Finally, we have binary variables indicating not-for-profit and for-profit ownership, where government-owned hospitals are the reference group.

3.6 Additional analyses

As discussed above, in addition to estimating the stochastic frontier cost function and inefficiency effects, we compute point estimates for inefficiency levels for all hospitals in all of the study years. In addition to reporting means for these values by year, we examine the correlation between these inefficiency effects and each hospital's occupancy rate and average length of stay.

4 Results

The mean characteristics of hospitals used in our analysis are found in Tables 1 and 2. Table 3 includes results for testing the appropriateness of pooling subsets of the data. We report the coefficients of the cost function and inefficiency estimates for urban and rural hospitals in Tables 4 and 5, respectively. These tables also contain the results of the appropriateness of the model specification.[11] The mean inefficiency estimates for each of the years are reported in Table 6.

In Tables 1 and 2, we present mean values for three time periods and for each of four types of hospitals: urban high-TennCare, urban low-TennCare, rural high-TennCare, and urban low-TennCare.[12] High-TennCare hospitals are defined as those having greater than the median proportion of TennCare/Medicaid inpatients over all years, and low-TennCare hospitals are those having less than or equal to the median proportion of TennCare/Medicaid inpatients over all years. As the means indicate, there are important difference between rural and urban hospitals (Table 1 vs. Table 2) and hospitals with different TennCare loads (high-TennCare vs. low-TennCare). A comparison of total expenses and outputs between urban and rural hospitals suggests that urban facilities are, on average, much larger, with urban hospitals having total expenses that are at least four times higher on average than their rural counterparts. For all four types of hospitals, there appears to have been increases over time in outpatient visits, the price of capital, the price of labor, and the proportion of Medicare admissions, but only rural hospitals saw a large percentage decline in inpatient days over the same period.

A few other changes in the mean values of key variables are also noteworthy. Both the mortality rate and HHI remained relatively constant over time, and both rural and urban hospitals taking a greater proportion of TennCare/Medicaid patients were, on average, in more concentrated markets, but there are no clear patterns regarding the mix of

[11] The specification tests follow suggestions outlined in Coelli et al. [56]. The generalized likelihood-ratio statistic associated with the null hypothesis involving a test of $g=0$ has a mixed chi-square distribution. The hypothesis test on the second-order coefficients from the translog uses a generalized likelihood ratio test,

[12] The tests for pooling lead to this division of urban and rural hospitals, as described below.

for-profit, not-for-profit, and public hospitals.[13] All four groups of hospitals saw some increase in the proportion of inpatient admissions and outpatient visits funded by TennCare in the period immediately following the program's implementation, with more dramatic change on average for urban hospitals.

The preceding discussion assumes that Tennessee hospitals' efficiency has been affected by their TennCare patient loads.[14] In theory, there may also be differences in the production technology and operating objectives of for-profit, not-for-profit, and government owned facilities and/or differences between urban and rural hospitals. It may therefore be inappropriate to pool all hospitals together to build a single efficient frontier. To address this concern of comparability, we conduct a series of generalized likelihood ratio tests using $\lambda = -2\{\ln[L(\mathrm{H}_0)] - \ln[L(H_1)]\}$, where $L(\mathrm{H}_0)$ is the log-likelihood function for the null hypothesis and $L(\mathrm{H}_1)$ is the log-likelihood function for the alternative hypothesis. The test statistic follows a chi-square distribution with degrees of freedom equal to the difference in parameters estimated under the alternative and null hypotheses.

All tests were conducted separately for hospitals with a higher vs. lower proportion of TennCare/Medicaid patients. The first two lines of Table 3 show the results of a test for pooling of for-profit, not-for-profit, and government facilities. For both high- and low-TennCare/Medicaid hospitals, the null hypothesis that pooling is appropriate is not rejected. Similarly, lines three and four of Table 3 consider pooling of urban and rural facilities and the test result clearly shows that separate analyses should be conducted for urban and rural facilities. The last four lines of Table 3 examine whether we can consider groups of years instead of a single binary indicator for each year in the inefficiency effects part of the model. The three periods considered are pre-TennCare (1990–1993), early TennCare (1994–1997) and late TennCare (1998–2001). A model with period-level indicators (the restricted model under the null hypothesis) is compared with a model containing a binary indicator for each year (the unrestricted model under the alternative hypothesis). The results fail to reject pooling of years into periods. However, yearly indicators are still useful for they provide more insights into the evolutionary effects of TennCare over time. Thus, we use binary variables for each year in the estimation of the inefficiency effects but frame some of our discussion in terms of the three periods.

Two additional hypotheses are considered, where the results for each subgroup of hospitals are presented near the bottom of Tables 4 and 5. First, as noted above, we test for whether g equals 0 and the coefficients on the inefficiency explanatory variables (d) are jointly insignificant, allowing us to efficiently estimate the model using OLS.[15] We reject the null hypothesis for all rural hospitals and for urban hospitals with a larger share of TennCare/Medicaid patients, suggesting that there are inefficiency effects in hospital costs. The failure to reject the null for urban hospitals with fewer TennCare/Medicaid admissions is not surprising given the lack of statistical significance of the coefficient estimates for this model.

Second, using a likelihood ratio test, we test the null hypothesis that the Cobb–Douglas functional form of the cost function is appropriate by testing that the second-order coefficients from the translog are jointly equal to 0. We find that the null hypothesis is not rejected, which suggests that the Cobb–Douglas is the appropriate functional form. This is not surprising given that the panel spans in excess of a decade, and thus is long-run in nature. The short-run constraints which limit technology use, input substitutability, etc., have likely been resolved, rendering the coefficients on the cross-product terms from Eq. 4 statistically insignificant.

Tables 4 and 5 allow for a four-way comparison of factors influencing costs and inefficiency for Tennessee hospitals according to their location in urban or rural area and whether they had high-TennCare load (>median TennCare/Medicaid inpatient proportion) or low-TennCare load (≤median TennCare/Medicaid inpatient proportion). The cost function coefficient estimates on the output measures and the capital input price are statistically significant at the 5% level and consistent with economic theory.[16] Both inpatient and outpatient days increase costs with the former having a much larger and positive coefficients than the latter for all four hospital types (urban/rural and high/low TennCare). However, each additional inpatient or outpatient day adds more costs for

[13] The were some changes in ownership over time that are reflected in the proportions of different facility types in different periods. When examining the data from 1990–2001, we found 25 instances in which hospital changed ownership type. Of these, there was a net increase over time of two not-for-profit hospitals, a net loss of three for-profit hospitals, and no net change in government-owned facilities. The net increase in not-for-profit entities was split between urban and rural areas (one hospital each). The net loss in for-profit facilities involved one rural and two urban hospitals. There was a two hospital increase in rural government hospitals and a two hospital decrease in urban government hospitals.

[14] The sample was also split into facilities with above and below median levels of outpatient TennCare/Medicaid visits and the analyses were conducted using those samples. The results were not qualitatively different from those presented in Section 4 and, therefore, are not presented.

[15] The critical values were obtained from Kodde and Palm [74].

[16] We tested for stationarity of the dependent variable for the full sample using the test developed by Maddala and Wu [73] for use with an unbalanced panel. The null hypothesis for this test is that the series is non-stationary. We tested the model with one lag, the model with one lag and a drift, and the model with one lag and a trend. In all three cases, the null hypothesis of non-stationarity was strongly rejected (p<0.0001).

Table 1 Mean characteristics of urban hospitals (1990–2001)

Variable	>Median Medicaid/TennCare			≤Median Medicaid/TennCare		
	1990–1993	1994–1997	1998–2001	1990–1993	1994–1997	1998–2001
Total expenses ($)	51,796,726	66,299,827	92,836,632	77,827,018	88,109,190	107,383,432
Outputs and input prices						
Total inpatient days	45,776	43,525	45,647	70,921	55,176	57,105
Total outpatient visits	60,416	65,773	98,995	69,241	86,015	98,782
Price of capital	19,201	22,331	36,388	21,243	29,190	34,003
Wages plus benefits	78,665	76,716	72,305	32,744	36,387	42,940
Quality of service and patient mix						
Medicare case-mix	1.2277	1.3079	1.4018	1.3374	1.4091	1.5272
% AMA approval for residencies	17.24	26.15	39.71	17.95	23.08	33.33
% Affiliated with Medical School?	20.69	23.08	30.88	17.95	23.08	36.27
% Mortality rate	2.52	2.58	3.03	3.28	3.79	3.48
% Outpatient visits that are ER visits	53.66	42.63	38.35	48.85	40.22	35.63
Market and hospital characteristics						
Population of County/10,000	18.4780	20.6059	23.9589	37.0910	31.7872	40.7880
Mean per capita personal income/10,000	1.6631	2.0427	2.5346	1.9318	2.3790	2.8816
HHI for County	0.4296	0.5108	0.5132	0.2356	0.2587	0.2238
% Medicaid/Tenncare inpatient admissions or discharges	23.93	27.42	27.30	9.26	12.59	12.31
% Medicaid/Tenncare outpatient visits	20.11	25.55	26.30	10.60	13.98	14.39
% Medicare inpatient admissions or discharges	34.41	40.89	42.18	43.75	47.88	51.07
% Medicare outpatient visits	27.87	29.84	25.60	27.48	29.46	29.80
% For-profit	18.97	40.00	23.53	35.90	36.26	23.53
% Not-for-profit	56.90	41.54	60.29	46.15	51.65	58.82
% Occupancy rate	45.29	45.02	37.90	45.38	44.40	40.76
Average length of stay	5.5790	5.0422	4.8398	6.7199	6.0573	5.1867
Number of observations		191			271	
Number of hospitals		27			38	

urban, low-TennCare hospitals than for urban hospitals with a high TennCare load. For rural hospitals, the opposite is observed, with each additional day adding more costs to rural high-TennCare hospitals than to rural low-TennCare ones.

The coefficient on the price of capital is positive and significant but the coefficients on the two medical education variables are insignificant due, in part, to the high pairwise correlation (r=0.587) between the two variables. While largely lacking statistical significance, the mortality rate and proportion of outpatient visits that are ER Visits are significant in two cases; a higher mortality rate is associated with higher costs for urban hospitals with fewer TennCare patients, and the proportion of outpatient visits that are ER t2.1 **Table 2** Mean characteristics of rural hospitals (1990–2001)

	Variable	>Median Medicaid/TennCare			< = Median Medicaid/TennCare		
t2.3		1990–1993	1994–1997	1998–2001	1990–1993	1994–1997	1998–2001
t2.4	Total expenses ($)	11,920,695	17,575,988	21,651,363	9,882,070	13,099,698	15,078,123
t2.5	Outputs and input prices						
t2.6	Total inpatient days	13,860	12,879	11,881	12,686	10,983	9,164
t2.7	Total outpatient visits	24,160	36,446	42,674	19,536	25,796	27,752
t2.8	Price of capital	9,699	12,766	17,924	11,424	11,852	14,080
t2.9	Wages plus benefits	26,435	30,387	35,532	24,171	29,824	33,471
t2.10	Quality of service and patient mix						
t2.11	Medicare case-mix	1.0400	1.1128	1.1239	1.0530	1.0750	1.0868
t2.12	% AMA approval for residencies	0.00	0.00	4.10	0.00	1.37	0.00
t2.13	% Affiliated with Medical School?	6.17	5.50	16.39	0.00	1.37	10.47
t2.14	% Mortality rate	2.87	3.13	3.01	3.35	3.54	3.27
t2.15	% Outpatient visits that are ER visits	55.63	41.80	39.75	59.83	49.88	61.97
t2.16	Market and hospital characteristics						
t2.17	Population of County/10,000	3.0508	3.5336	3.6662	2.6683	2.9475	2.9939
t2.18	Mean per capita personal income/10,000	1.3904	1.7196	2.0318	1.3846	1.6861	1.9747
t2.19	HHI for County	0.7891	0.7726	0.7990	0.6887	0.6781	0.7169
t2.20	% Medicaid/Tenncare inpatient admissions or discharges	23.91	24.97	24.23	14.04	14.98	13.29
t2.21	% Medicaid/Tenncare outpatient visits	23.23	26.35	26.42	17.25	20.34	22.89
t2.22	% Medicare inpatient admissions or discharges	42.36	47.60	52.28	50.01	67.33	65.27
t2.23	% Medicare outpatient visits	30.45	33.48	32.41	35.66	34.38	42.18
t2.24	% For-profit	39.51	37.61	37.70	36.84	27.40	19.77
t2.25	% Not-for-profit	23.46	26.61	29.51	43.42	50.68	52.33
t2.26	% Occupancy rate	38.79	32.36	28.74	34.41	34.79	30.48
t2.27	Average length of stay	5.0251	4.1270	3.8422	5.1528	4.6779	4.5022
t2.28	Number of observations		312			235	
t2.29	Number of hospitals		41			30	

visits increases costs for rural hospitals with high TennCare patient loads. This suggests that the variables are serving as proxies for unmeasured patient acuity, but the mortality rate may also be a proxy for quality. The county-level income and population variables are generally not significant, which may be partially attributable to the segmentation of the sample into urban and rural areas.

Turning to the inefficiency estimates, the year prior to the implementation of TennCare, 1993, serves as the reference period. To ease in the comparison of the four models, the point estimates for the inefficiency coefficients on the year indicator variables (found in Tables 4 and 5) from 1993 to 2001 are shown in Graph 1. As expected, high-TennCare hospitals had larger inefficiency changes in the 1993–2001 period when compared to low-TennCare ones in general. However, high-TennCare urban hospitals experienced *efficiency gains* in most years, while high-TennCare rural hospitals saw *losses in efficiency*. The inefficiency changes for low-TennCare hospitals were much smaller in magnitude, and were not significantly different from zero for urban hospitals.

One potential concern in interpreting the coefficient estimates on the time indicators is that the late TennCare period of 1998–2001 corresponds with the BBA of 1997, which generally tightened reimbursement levels for Medicare inpatients. As shown in Tables 1 and 2, Medicare patients on average make up more than one third of admissions for all groups of hospitals, raising the likelihood that changes in reimbursement would affect efficiency levels. Given this issue, it is useful to explore inefficiency changes in 1994–1997 and the post-BBA period of 1998–2001 separately.

Revisiting the results in Tables 4 and 5, low-TennCare hospitals appear to have inefficiency levels that were virtually unchanged from 1994–1997. In contrast, hospitals with a larger proportion of TennCare patients in 1994–1997 experienced significant efficiency changes: decreased inefficiency for urban hospitals and increased inefficiency for rural hospitals. In the late-TennCare period of 1998–2001, urban high-TennCare hospitals maintained or increased their efficiency gains but rural hospitals experienced efficiency losses regardless of whether their TennCare populations were high or low. In the case of urban hospitals, increases in TennCare patients and the associated costs appear to have been offset by changes at the facility level that increased efficiency. In contrast, rural hospitals

Table 3 Likelihood ratio tests for pooling

Null hypothesis	Subgroup	Test statistic	*df*	*P* value	Test result
Pooling facilities by ownership type is appropriate	Greater than median Medicaid/ TennCare	λ=58.7844	48	0.1369	Fail to reject H_0
Pooling facilities by ownership type is appropriate	Less than or equal median Medicaid/TennCare	λ=36.0045	48	0.8988	Fail to reject H_0
Pooling urban and rural facilitites is appropriate	Greater than median Medicaid/ TennCare	λ=234.0599	27	<0.0001	Reject H_0
Pooling urban and rural facilitites is appropriate	Less than or equal median TennCare	λ=128.9476	27	<0.0001	Reject H_0
No significant difference between pooling years into three distinct periods and year binary indicators	Greater than median Medicaid/ TennCare, Urban	λ=7.1131	9	0.6233	Fail to reject H_0
No significant difference between pooling years into three distinct periods and year binary indicators	Greater than median Medicaid/ TennCare, Rural	λ=2.7865	9	0.9722	Fail to reject H_0
No significant difference between pooling years into three distinct periods and year binary indicators	Less than or equal median Medicaid/TennCare, Urban	λ=7.7669	9	0.5578	Fail to reject H_0
No significant difference between pooling years into three distinct periods and year binary indicators	Less than or equal median Medicaid/TennCare, Rural	λ=11.5908	9	0.2374	Fail to reject H_0

were unable to overcome the burden of increased TennCare populations and saw increased levels of inefficiency.

To check for whether our findings for the period immediately following TennCare's implementation are sensitive to the inclusion/exclusion of the post-BBA period from the sample, we re-estimated the models (results not shown but available from authors upon request) using only data from the pre-BBA period (1990–1997). When doing so, we found results similar to those described above for the period immediately following TennCare's implementation: rural hospitals with more TennCare patients saw increased inefficiency levels while urban hospitals with more TennCare patients saw reductions in inefficiency. The only difference was for urban hospitals with low TennCare loads; using the longer period, we see no change in inefficiency, while using the shortened period leads to a modest increase in inefficiency initially (1994 and 1995), followed by a decrease in inefficiency (1996 and 1997).

Finally, we find that increased market concentration (measured by HHI for the County, where higher values indicate more concentrated markets) was not associated with efficiency changes except for rural, low-TennCare hospitals. This finding suggests that the level of concentration is not important for explaining the level of inefficiency of most hospitals but we cannot rule out the notion that rural low-TennCare facilities are exercising market power. After stratifying on rural/urban location and higher/lower TennCare populations, the proportion of TennCare and Medicare patients had no average overall effect on efficiency. With one exception, the same is true for ownership type.

The mean estimated inefficiency scores are given in Table 6 for the four subsamples considered. Considering the overall estimates first, it appears that hospital inefficiency increased over the entire 1990–2001 period. However, from 1993 (the last year before TennCare) to 2001, there was an almost five percentage point gain in hospital efficiency. Inefficiency levels in the 1994–1997 post-TennCare period were modestly lower than 1993, and they fell more notably in 1999 and 2001.

Overall, mean inefficiency for Tennessee hospitals was 20.6%. It is important to note that the inefficiency levels for the different subsamples varied subtantially, as discussed in more detail below, with mean inefficiency levels for urban facilities and high-Medicaid/TennCare rural facilities at less than 10% and mean inefficiency levels for rural facilities with low-Medicaid/TennCare patient loads at 60.9%. The aggregate mean value of 20.6% is certainly heavily influenced by the effect of the low-Medicaid/TennCare rural facilities. Unfortunately, it is difficult to compare these estimates to those in prior works given that no other study breaks down the population of facilities using the same subgroups and/or use the broad range of facilities considered in this study. For instance, Rosko [31] finds mean inefficiency estimate of 13.1% for private, urban, teaching hospitals for the period 1990–1999, a value that is lower than the overall mean in our study but higher than the mean for three of our four subgroups. The overall mean inefficiency level for Tennessee hospitals is consistent with estimates by Folland and Hofler [45], where the sample is more inclusive but from a single year, 1985.

The results based on separate subsamples reveal that hospitals in the different groups were operating at different levels of inefficiency prior to the implementation of TennCare and in later years. An examination of overall efficiency in the 1990–2001 period for each hospital type reveals that urban facilities have inefficiency levels of 7–8%. They are modestly more efficient than rural facilities

Table 4 Cost function and inefficiency estimates for Ln(total expenses) for urban hospitals

Variable	>Median Medicaid/TennCare		≤Median Medicaid/TennCare	
	Coefficient estimate	*t* ratio	Coefficient estimate	*t* ratio
Cost function estimates				
Intercept	−1.0630	−1.0714	−1.9106	−6.2338
Ln(total inpatient days)	0.6968	1.6674	0.7290	39.5917
Ln(total outpatient visits)	0.0858	0.1894	0.1190	3.6784
Ln(price of capital)	0.5068	1.9400	0.1449	4.0927
AMA approval for residencies	0.1248	0.1666	−0.0302	−0.6193
Affiliated with Medical School?	−0.1088	−0.1293	0.0113	0.2336
Mortality rate	−0.9931	−0.9931	2.1760	2.2683
% Outpatient visits that are ER visits	−0.0134	−0.0183	−0.0701	−1.0609
Personal income in County/10,000	−0.0316	−0.0357	0.0257	1.1912
Population of County/10,000	0.0065	0.3425	−0.0009	−1.3043
Inefficiency estimates				
Intercept	−0.0544	−1.0004	0.0668	0.2016
1990	−0.1863	−1.5203	−0.0943	−0.0970
1991	−0.3488	0.4635	−0.2160	−0.9853
1992	−0.1127	1.9847	−0.2617	0.6698
1994	−0.0668	0.9072	0.0003	0.8785
1995	−0.0941	0.5825	0.0033	1.1205
1996	−0.0899	0.5105	−0.0015	1.4798
1997	0.0475	2.3421	−0.0059	1.3672
1998	−0.1182	0.1877	−0.0883	0.6336
1999	−0.3393	−2.2097	−0.0571	0.8683
2000	−0.1591	−0.4094	−0.0130	1.3625
2001	−0.1102	0.5288	−0.0840	0.6146
HHI for County	0.2482	0.3092	0.0420	0.4211
% Medicaid/Tenncare inpatient admissions	−0.0161	−0.2581	0.0131	0.0334
% Medicaid/Tenncare outpatient visits	0.0296	0.3727	−0.1540	−0.2457
% Medicare inpatient admissions	0.0444	0.7931	−0.1793	−0.4533
% Medicare outpatient visits	−0.0254	−0.3116	0.0526	0.1584
Not-for-profit	−0.0458	−0.8841	0.0014	0.0263
For-profit	−0.0522	−0.9452	−0.0940	−1.2961
Number of observations	191		271	
Number of hospitals	27		38	
	Test statistic	5% Crit. Val.	Test statistic	5% Crit. Val.
H_0: $\gamma=\delta_1=\ldots=\delta_{19}=0$	30.95	30.81	13.94	30.81
H_0: $\beta_{ij}=0$ for all $i \le j=1, 2, 3$	9.45	11.07	4.61	11.07

with large numbers of TennCare/Medicaid patients, with average inefficiency levels of 9.7%. However, as noted above, rural facilities with relatively lower TennCare/Medicaid loads have much larger inefficiency levels: 60.9% over the study period. Changes over time in inefficiency levels also differ across groups. Consistent with the inefficiency effects reported in Tables 4 and 5, urban facilities with higher TennCare loads saw the largest average gains in efficiency, while both rural and urban facilities with fewer TennCare patients saw much smaller efficiency changes. Perhaps most surprisingly, rural hospitals with high TennCare loads saw increases in mean inefficiency over the study period.

As noted above, prior researchers found lower occupancy rates and average length of stay in Tennessee hospitals after TennCare went into effect in 1994, and this result was confirmed by the descriptive statistics on these two variables shown in Tables 1 and 2. An examination of pairwise correlations (r) between predicted hospital level inefficiency levels in each year and occupancy rate revealed a significant ($p<0.0001$) negative relationship ($r=-0.186$). This suggests that hospitals with lower occupancy rates were also less efficient. When looking at the subgroups, this effect holds only for urban facilities. There was also a negative ($r=-0.112$) and significant ($p=0.0003$) correlation between average length of stay in the hospital and inefficiency for all four subgroups, indicating that the decreased length of the average stay is related to higher inefficiency levels. In theory, a shorter length of stay can be the result of greater

Table 5 Cost function and inefficiency estimates for Ln(total expenses) for rural hospitals

Variable	>Median Medicaid/TennCare		≤Median Medicaid/TennCare	
	Coefficient estimate	*t* ratio	Coefficient estimate	*t* ratio
Cost function estimates				
Intercept	−3.5890	−3.9749	−0.4347	−0.1130
Ln(total inpatient days)	0.5176	14.1145	0.4240	11.2583
Ln(total outpatient visits)	0.4551	5.3940	0.1602	3.5075
Ln(price of capital)	0.0365	1.9710	0.1650	6.5164
AMA approval for residencies	−0.1837	−0.2140	−0.0106	−0.0482
Affiliated with Medical School?	0.0764	1.0688	−0.0243	−0.3034
Mortality rate	−0.2429	−0.2403	−0.3688	−0.3921
% Outpatient visits that are ER visits	0.4414	2.0361	−0.0458	−0.9368
Personal income in County/10,000	0.0522	0.3286	−0.1067	−0.9965
Population of County/10,000	−0.0370	−1.2904	0.0923	5.2605
Inefficiency estimates				
Intercept	0.1693	0.3369	1.0629	0.2785
1990	−0.0071	0.5691	0.8433	0.8375
1991	0.0069	1.1220	−0.1565	1.8029
1992	0.0977	0.6514	−0.0801	2.4263
1994	0.1782	1.5201	−0.0144	2.1084
1995	0.1175	2.2507	0.0115	2.6603
1996	0.2140	1.1730	0.0728	1.7903
1997	0.1028	1.9397	−0.0190	2.1964
1998	0.1783	2.1932	0.0642	2.2003
1999	0.2061	2.3054	0.0703	2.0166
2000	0.2365	1.4415	0.0694	2.4971
2001	0.1365	−1.1995	0.1470	5.8771
HHI for County	−0.1635	−1.1995	0.2374	5.8771
% Medicaid/Tenncare inpatient admissions	−0.2866	−0.3543	−0.0497	−0.1169
% Medicaid/Tenncare outpatient visits	−0.1897	−0.2511	0.1937	0.8213
% Medicare inpatient admissions	−0.1822	−0.3827	−0.9256	−3.8918
% Medicare outpatient visits	−0.1680	−0.5687	0.1056	1.0209
Not-for-profit	−0.4237	−1.5837	0.0101	0.2404
For-profit	0.0540	0.4606	−0.1148	−2.1712
Number of observations	312		235	
Number of hospitals	41		30	
	Test statistic	5% Crit. Val.	Test statistic	5% Crit. Val.
H_0: $\gamma=\delta_1=\ldots=\delta_{19}=0$	42.96	30.81	80.89	30.81
H_0: $\beta_{ij}=0$ for all $i\leq j=1, 2, 3$	9.85	11.07	10.93	11.07

hospital efficiency, with patients being turned over faster and discharged earlier than before. However, our results suggest that if the shorter length of stay is accompanied by a marked decrease in occupancy, a higher level of inefficiency can result.

5 Discussion and conclusion

Our study measures the effect of TennCare on the efficiency of hospitals in Tennessee. The multiple-output stochastic frontier estimates allow us to consider factors that affect hospital costs as well as factors that are predictive of inefficiency levels for Tennessee hospitals. In modeling the effect of TennCare on hospital inefficiency, we test a series of hypotheses to confirm the appropriateness of the stochastic frontier approach and test hypotheses regarding pooling/splitting of the sample. In addition, our finding of a large number of statistically significant variables with expected signs in general lends credence to the validity of our theoretical approach and model specification.

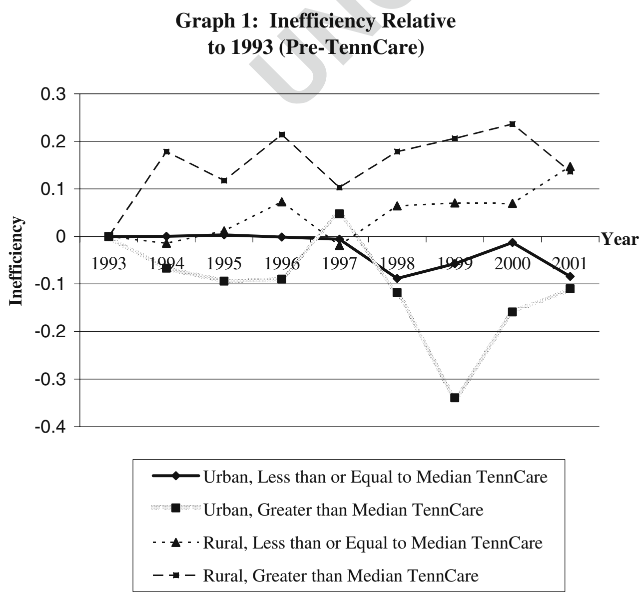
Overall, we find modest increases in overall efficiency in the four years immediate after the beginning of TennCare (1994–1997), with additional small increases in efficiency in the late TennCare years (1998–2001). However, these small increases in efficiency since 1993 for Tennessee hospitals in general mask the different results experienced by urban and rural facilities with larger TennCare inpatient loads. The results for urban facilities with a greater-than-median proportion of

Table 6 Mean inefficiency estimates by year

Year	All		Urban				Rural			
			>Median Medicaid/ TennCare		≤Median Medicaid/ TennCare		>Median Medicaid/ TennCare		≤Median Medicaid/ TennCare	
	Inefficiency	*N*	Inefficiency	*N*	Inefficiency	*N*	Inefficiency	*N*	Inefficiency	*N*
1990	0.147239	64	0.044682	14	0.016070	18	0.023670	17	0.540407	15
1991	0.168315	72	0.000112	14	0.008288	17	0.056052	22	0.565424	19
1992	0.197761	82	0.073945	16	0.005102	23	0.083103	21	0.598669	22
1993	0.241909	75	0.140803	14	0.112257	20	0.056109	21	0.637424	20
1994	0.224136	84	0.102205	15	0.108874	24	0.121175	26	0.606887	19
1995	0.201575	77	0.082477	15	0.113254	20	0.082518	26	0.617096	16
1996	0.229570	85	0.098206	16	0.110542	23	0.139151	28	0.639078	18
1997	0.217320	92	0.189120	19	0.099723	24	0.081135	29	0.582698	20
1998	0.214056	97	0.080296	17	0.045572	26	0.113806	30	0.616639	24
1999	0.199615	97	0.000074	17	0.069464	26	0.124771	32	0.616483	22
2000	0.221332	91	0.061613	17	0.095369	27	0.142739	26	0.609888	21
2001	0.193420	93	0.074959	17	0.047606	23	0.091250	34	0.658755	19
Average	0.206157	1009	0.080651	191	0.071097	271	0.097195	312	0.608579	235

TennCare patients generally support the prediction of the X-inefficiency theory that the largest gains in a hospital's operating efficiency are not evident at first and begin to emerge later after hospitals have had time to adjust to a major health care reform. However, the late TennCare period of 1998–2001 coincided with the enactment of Medicare BBA reforms making it difficult to disentangle the observed efficiency gains in the 1998–2001 period from the effects from changes in Medicare reimbursement rates in that same period.

In the two post-TennCare periods studied, high-TennCare urban facilities saw efficiency gains but rural facilities with high numbers of TennCare patients experienced efficiency declines. Rural hospitals are small and structurally vulnerable to external forces that can adversely affect their profit margin. In general, they lack the financial resources, managerial know-how and experience to manage adverse impact beyond their control when compared to their urban counterparts. Their small size also deprives them the economies of scale to "weather the storm" of the external pressures imposed by a sudden change in reimbursement environment. Our results strongly suggest that rural hospitals are indeed a different breed and the impact of policy changes on them may be quite different from those experienced by urban hospitals. Board directors and hospital administrators in rural areas tend to "live in the community." Knowing their neighbors might have prevented them from cream skimming by reducing TennCare loads and/or reducing labor costs by laying off workers and/or paying them less.



Graph 1 Inefficiency relative to 1993 (Pre-TennCare)

Given the high costs of inpatient care, the modest efficiency gains for high-TennCare urban hospitals should prove to be welcome news to government officials and private contractors who manage the program. This good news must be tempered by the fact that efficiency in rural hospitals decreased in the years following TennCare's implementation. The data also indicate that trends in decreasing occupancy rates and average length of stay are likely driving up hospital inefficiency levels over time across the board.

In interpreting the results, it is important to realize that we are assuming that the relatively small additions in the proportion of TennCare-insured patients experienced by rural hospitals and the larger increase in the proportion of TennCare-insured patients experienced by urban hospitals are just as costly on average as patients in the pre-TennCare years (in inflation adjusted terms, as total costs are normalized by the price of labor). If the new TennCare patients are more costly, on average, the measurement may show up as an increase in inefficiency. We do not have patient-level data that allow us to sort out the costs of TennCare patients relative to other patient types over time. However, our finding of efficiency gains for urban hospitals with the largest increases in TennCare loads suggests that it is unlikely that these patients were markedly more expensive than other patients. The data also reveal that year-to-year changes in average total costs normalized by the price of labor vary somewhat from year to year, but there is no apparent upward trend.

In addition to continuing to follow changes in the efficiency of hospitals as the TennCare program evolves, it is important that future research focus on several areas neglected by our study. We limit our analysis to acute care hospitals with at least some outpatient visits and we explicitly exclude specialty hospitals such as psychiatric and rehabilitative hospitals. Future research may wish to consider the effect of TennCare on these facilities as they may have reacted differently to the TennCare experiment than traditional acute care hospitals. Due to data limitations, our work also fails to control for the availability of complements and substitutes for hospital care, such as urgent care centers and freestanding outpatient surgery centers. If these factors are predictive of hospital costs or efficiency levels and are correlated with included explanatory variables, the estimated coefficients on these explanatory variables may be inconsistent.

Finally, there is lingering concern about the effects of quality differences and differences in product-mix on the inefficiency estimates. As noted above, beyond the unadjusted mortality rate and two measures of engagement in medical education, our data do not allow for a direct measure of quality. Similarly, we attempt to control for differences in the inpatient product mix by using the Medicare Case-mix Index and differences in the outpatient product mix by controlling for the proportion of outpatient visits that are to the emergency department, but there may be additional heterogeneity in the product mix. By stratifying the sample on the proportion of TennCare/Medicaid patients and urban/rural location, we increase the comparability of the products produced by each hospital in each subsample. However, any remaining unmeasured quality and product differences will show up in the error term for the model of costs and influence the inefficiency estimates. While not directly applicable to our study, we can find some solace in the work by Rosko and Mutter [53] who consider SFA estimates of US hospitals and find little difference between inefficiency estimates from models with and without the sort of outcome measures of quality that are omitted from our analysis.

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