Analysis of Hospital Production: An Output Index Approach*

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Abstract

In this study, a new model of hospital costs is developed and estimated, utilizing an output index. This theoretically appropriate output index is constructed to accurately reflect the differentiated nature of hospital care by employing both patient and diagnosis characteristics in its construction. Using this output index, we estimate a long-run translog cost function with a dataset of 320 California hospital for the year 2003. Our results show evidence of scale economies which are exhausted in the range of 228-277 beds. Point estimates of scale economies using the output index indicate that minimum efficient scale is reached at a level 4-30% higher than previously employed output measurement techniques. There is evidence of scope economies between primary and secondary care as well as tertiary and outpatient care, and a within-category estimator suggests the presence of scope economies within our aggregated output categories. Simulations using our estimated cost function indicate that the combination of small hospitals generates cost efficiencies of approximately 6-20%. Finally, our estimates indicate that Medicare reimbursement rates are below marginal cost for the average hospital, though the imprecision of our estimates cannot rule out profitability.

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1. Introduction

The health care sector represents one of the most important sectors of the U.S. economy, accounting for $2 trillion or 16 percent of U.S. gross domestic product in 2005 alone (National Coalition on Healthcare http://www.nchc.org/). Within the health care sector, hospital spending represents almost one-third of total spending and is expected to grow at a rate greater than that of GDP over the next 5 years [Shactman et. al. (2003), Smith et. al. (2005)]. Because of this, economists and policymakers are interested in understanding the relationships between the size and diversity of hospital production so as to surmise the potential for efficiency gains through facility consolidation or reconfiguration.

Over the last two decades, the hospital industry has seen a considerable amount of consolidation activity as well as a substantial number of facility closures. The search for cost efficiencies from consolidation was cited as one of the major reasons for the over 1000 hospital mergers and acquisitions between 1994-2003 and was used as a defense justification in six hospital merger cases tried by the antitrust authorities since 1990 [ABA Handbook (2003)]. In addition, the FTC/DOJ merger guidelines specifically state that when examining mergers larger than 100 beds they specifically weigh any cost considerations resulting from economies of scale against potential price increases resulting from market consolidation. Furthermore, the mandated closure of hospital facilities has recently become a pressing policy concern in states such as New York, which recently ordered the closing of 9 hospitals and the reconfiguration of 48 others.

Given this high level of consolidation and reconfiguration activity in the hospital industry, as well as the explicit recognition of regulators as to the existence of cost efficiencies, one might surmise that empirical evidence should support the findings of substantial cost efficiencies brought about by increases in both the magnitude of operations (scale economies) and the variety of services offered (scope economies) by hospitals. However, despite a large literature estimating hospital costs, few firm conclusions can be drawn regarding the extent of scale and scope economies in this important industry. Moreover, despite the substantial changes that have occurred in this industry in recent years, hospital costs studies, especially for U.S. hospitals, are for the most part old and outdated [Dranove (1998)].

As Breyer (1987) notes, given the number of outputs produced by a hospital, it is impossible to adequately account for hospital case heterogeneity while also maintaining a functional form sufficiently flexible to allow for theoretically sound estimates of scale and scope economies. Because of this, researchers typically aggregate output into categories based on varying dimensions. Past studies are, however, inconsistent with each other in terms of the means by which they aggregate output into output categories, with minimal consideration given to the theoretical conditions necessary for such aggregation. In addition, within each output category, past treatment of each case has assumed uniformity across cases, regardless of its severity or the characteristics of the individual receiving care. These inconsistencies may partially contribute to the lack of hard evidence regarding the extent of scale and scope economies in the hospital industry.

In this study, a new model of hospital costs is developed and estimated, utilizing an output index. This theoretically appropriate output index is constructed to accurately reflect the highly differentiated nature of hospital care by employing both patient and diagnosis characteristics in its construction. Using this output index, we estimate a long-run translog cost function with a dataset of 320 California hospitals for the year 2003. Our results show evidence of scale economies which are exhausted in the range of 228-277 beds. Point estimates of scale economies using the output index indicate that minimum efficient scale is reached at a level 4-30% higher than previously employed output measurement techniques. There is evidence of scope economies between primary and secondary care as well as tertiary and outpatient care, and a within-category estimator suggests the presence of scope economies within our aggregated output categories.

The cost function estimates are then employed for policy analysis. We consider two policy questions: cost savings due to merger, and the marginal profitability of Medicare reimbursements for various hospital services. Simulations using our estimated cost function indicate that the consolidation of small hospitals generates substantial cost efficiencies of up to 20%. Finally, our estimates indicate that Medicare reimbursement rates are below marginal cost for the average hospital, though the imprecision of our estimates cannot rule out profitability.

2. Previous Literature

The econometric analysis of hospital costs forms a cornerstone of empirical health economics. There is a fairly substantial literature estimating hospital costs; however, the results from these studies are by no means definitive. As Dranove (1998) notes, despite a long history of empirical estimation of cost functions, a troubling aspect is its general inconclusiveness.

This early literature is, for the most part, based upon ad hoc regression specifications in which it is assumed that the impact on unit costs of various cost determinants is linear and additively separable. Typically some measure of average costs is regressed upon beds and beds squared along with a variety of other control variables. Cowing et. al. (1983) provide a summary of this literature whose general conclusion is the exhaustion of scale economies at approximately 200 beds.

More recent contributions usually use specifications which are either neoclassical cost functions or variations on neoclassical forms. Such forms were developed from properties and propositions about cost structures which are consistent with economic theory. The majority of these studies estimate a short-run cost function with some proxy for capital stock included in their function. As a measure of output, they typically group together patient days or discharges into groups such as Medical/Surgical care, Pediatric care, and Obstetric care or group by inpatient discharges and outpatient visits. In most studies a case-mix variable is also included in the specification to account for the fact that hospitals differ in the case complexity of the patients that they treat, however, as Breyer (1987) notes, misclassification with regard to type of care with the addition of a case-mix variable casts considerable doubt on the validity of the parameter estimates in these studies.

The earliest versions of these neoclassical estimations were done by Cowing and Holtman (1983) and Conrad and Strauss (1983). Cowing and Holtman measure output in patient days for 5 output categories based on service type. They find evidence of short run scale economies and limited evidence of scope economies. Conrad and Strauss estimate a function using Medicare, non-Medicare and child inpatient days and find that hospital cost functions exhibit constant returns to scale. Vita (1990) estimates a function similar to that of Cowing and Holtman and finds diseconomies of scale and no evidence of economies of scope, although he mentions that actual long run scale economies may be larger than his estimates indicate

Grannemann et. al. (1986) use a hybrid functional form which incorporates the features of both the ad hoc and structural functional forms. This form is employed in order to allow the use of nine output categories which include patient day, discharge and visit measures across hospital departments. A discussion of whether their function corresponds to a long-run or short-run function is absent from their paper. Of these nine departments, they find evidence of scale economies only in emergency departments. Vitaliano (1987) uses both a quadratic and a logarithmic cost function and finds evidence of returns to scale, however, his output measure is beds which is normally thought of as a proxy for capital stock rather than an output measure in and of itself.

Fournier and Mitchell (1992) employ 5 output measures classified based on hospital department and estimate a short-run translog function using the book value of equipment as their measure of capital. They find statistically insignificant overall and product specific economies of scale but significant economies of scope. Gaynor and Anderson (1995) estimate a translog function using inpatient admissions and outpatient visits and find evidence of scale economies in the context of a model which takes into account a hospital's problem of maintaining standby capacity.

Carey (1997) departs from the neoclassical approach in her use of a panel specification. She finds evidence of scale economies in large hospitals which she conjectures may be due to mismeasured quality. Dranove (1998) estimates a semi-parametric cost function using inpatient and outpatient discharges and finds the exhaustion of scale economies at around 200 beds

Although most of the preceding literature has focused on the estimation of short-run variable cost functions, papers by Keeler and Ying **(**1996**)** and Preyra and Pink (2006) estimated long run cost functions. These two papers differ greatly in the means by which they estimate such functions. Keeler and Ying attempt construct a measure of capital price based on gross plant and equipment assets and a set depreciation schedule and interest rate. They find evidence of slight decreasing returns to scale. Using a dataset of Canadian hospitals, Preyra and Pink depart from the conventional structural cost estimation and employ a quadratic functional form using the assumption that input prices are uniform across hospitals. They estimate a short-run cost function and differentiate this function with respect to capital to get an optimal value of capital (beds) as a function of their outputs. Their results show evidence of short-run diseconomies of scale but their long run function shows evidence of economies of scale. Furthermore they find evidence of economies of scope between primary and ambulatory care. Bilodeau et. al. (2000) test long-run costs minimization assumptions data on Quebec hospitals and find that these hospitals may behave in a way that precludes analysis assuming long-run cost minimizing behavior. However, given the market conditions under which Canadian hospitals operate, such behavior may not accurately represent the long-run behavior of their U.S. counterparts.

3. Cost Function Estimation and the Measurement of Output

The following section discusses production theoretic issues related to the estimation of a multiproduct cost function. We also briefly review measures which are commonly used to investigate the properties of such functions. For a more detailed discussion of commonly employed functional forms and their properties, see Appendix A.

3.1 Output Classification

The transformation function, F(**X, Y**) summarizes the process by which a vector of *m* inputs, **X**, are transformed into a vector of *n* outputs, **Y**. Using Shephard's Theory of Duality (1953) McFadden (1978) showed that given a transformation function, F(.) which is strictly convex in inputs, there exists a cost function C(**Y**,**w**) which is homogeneous of degree 1, nondecreasing, and concave in factor prices (**w**) in which all structural features of the transformation function are embodied. As McFadden notes, the cost function contains all of the information necessary to reconstruct the structure of production possibilities and is thus a "sufficient statistic" for the technology.

For firms producing few outputs, direct estimation of technological properties of production using a cost function requires little simplification of the output space. For firms producing many outputs, however, the "curse of dimensionality" typically necessitates the aggregation of outputs into groups to allow meaningful statistical analysis given available data. The multiproduct nature of a hospital necessitates such aggregation, as hospitals produce many, many outputs. For example, a common way of classifying hospital care is by diagnosis related group. There are currently 564 Diagnosis Related Groups (DRGs).

The aggregation of outputs into an output index vector means that the efficient transformation function can be written as F(**X, h(Y)**)=0, where **h**(Y) is an output index which aggregates outputs into a vector of dimension less than that of **Y**. As Brown et. al. (1979) detail, because $\partial F/\partial \mathbf{h} \neq 0$, the implicit function theorem guarantees the existence of a function *f*, such that **h**(**Y**)=*f*(**X**). This property, which enables the representation of the production structure with outputs on the left and inputs on the right is called separability.

Under separability, the cost function can be written as $C(\mathbf{h}(Y), w)$ and the ratios of the marginal cost of any two aggregated outputs,

$$\frac{\partial C(Y,w)/\partial Y_i}{\partial C(Y,w)/\partial Y_j} = \frac{\partial \mathbf{h}(Y)/\partial Y_i}{\partial \mathbf{h}(Y)/\partial Y_j}\left(= \frac{\partial F(X,Y)/\partial Y_i}{\partial F(X,Y)/\partial Y_j}\right)$$

are independent of input prices (and hence, inputs- see Hall (1973)). Thus the firm can choose its allocation of outputs independent of its allocation of inputs. This implies that with hospitals, one should be mindful that when aggregating outputs because within each output aggregation category each output should be similar with respect to the inputs required for the production of those outputs.

Previous attempts at hospital output measurement generally proceed by grouping hospital outputs based on inpatient discharges and outpatient visits or by diagnostic categories (e.g. medical/surgical, obstetrics, pediatric care etc.) and measuring output within each category using either the total number of patient days or the total number of discharges or visits within each category. A number of problems arise, however, when measuring output using such categorizations. The first has mainly to do with the satisfaction of the theoretical conditions necessary for output aggregation. HMOs and PPOs do not purchase specific medical procedures; instead they purchase what can be thought of as aggregates of "stand-by" capacity at each hospital which is to be customized to the specific condition of the hospitalized HMO/PPO member. While most hospitals provide a core group of procedures, as procedures become more specialized and complex, the number of hospitals providing such services typically decreases. This fact, coupled with the common distinctions in the rhetoric of health planners and practitioners about "primary", "secondary", "tertiary", implies that the type of care produced by hospital should be more appropriately grouped by the input intensiveness of the care received rather than by the hospital department in which one received it.

Given the specified aggregation conditions, we adopt the approach to classifying care taken by Preyra and Pink (2006) which classifies care according the level of inputs required to produce a given level of care, rather than using categories which correspond to care types differing greatly in their resource intensity (and thus input requirements). For example, past studies typically group hospital output into inpatient and outpatient category or which may group together seemly dissimilar diagnoses such as intensive care and transplant discharges with ear infections, and substance abuse/addiction discharges. Using the approach taken by Preyra and Pink, because tertiary and quaternary care require extensive diagnostic equipment and technical expertise and is often provided primarily at a teaching or university affiliated hospital, this type of care would be grouped into a separate category than primary care which requires non-specialized labor and low-cost capital assets. [1]

3.2 Output Definition

The extent to which hospitals differ in the types of cases being treated also complicates accurate measurement of hospital output. Because hospital care is highly differentiated not only by diagnosis or procedure but also by individual, a theoretically proper measure of hospital output should account for the types of cases being treated at

[1] Technological and Medical Advances have turned many medical procedures that once required overnight or extended stays into outpatient or short-stay episodes. Because of this, our care classification system does assign a positive level of tertiary care procedures to most hospitals in the data although it is quite small for hospitals with fewer than 25 beds.

each hospital. Thus, a precise measure of hospital output should take into account both the case-mix as defined by the types of procedures performed at a hospital, as well as the overall complexity and hospital-specific resource intensiveness of such cases. For example, imagine two hospitals that treat roughly the same number of heart attack patients, one with high costs and one with low costs. One might conclude that the high cost hospital is less efficient than the low cost hospital. However, if the high cost hospital typically treats patients requiring more complex (and presumably more costly) treatment, such a conclusion might be misleading. In the context of the analysis of scale economies, if larger hospitals treat more complex cases, mismeasurement of output in such a way will bias scale estimates downward.

We deal with this issue by constructing an output index which accounts for both the diagnosis and individual characteristics of each hospital consumer. Our goal is to take into account the highly differentiated nature of hospital care into an output measure which more closely accounts for the intricacies of each case. This approach has the advantage in that it measures hospital output using a uniformly chosen measure and thus improves upon the output definition problems associated with previous studies of hospital costs.

3.3 Multiproduct Cost Concepts

When constructing measures of scale for a multiproduct cost function, a major difficulty is that it possesses no natural single quantity over which costs can be averaged. In addition, a multiproduct cost function allows for complementarities between outputs which have no direct analogue in the single product case. With this in mind we briefly discuss a number of cost concepts proposed for investigation of multiproduct cost functions as defined by Baumol Panzar and Willig (1988). We make use of these measures (or slight modifications thereof) in our analysis of the properties of the estimated cost function.

The degree of scale economies is the elasticity of output with respect to the cost incurred to produce it. In the multiproduct case, returns to scale are defined as:

$$S_N(y) = \frac{C(y)}{\sum_{i=1}^{n} y_i \frac{\partial C(y)}{\partial y_i}} = \frac{1}{\frac{\partial \ln C(y)}{\partial \ln(y_i)}} \quad (1)$$

Using this measure, returns to scale are said to be increasing, constant or deceasing as S_N is greater than, equal to or less than unity, respectively. S_N can be interpreted as the elasticity of the output of the relevant "composite commodity" with respect to the cost needed to produce it.

Product Specific Economies of Scale can be defined as:

$$S_i(y) = \frac{C(y) - C(Y_{N-i})}{y_i \frac{\partial C}{\partial y_i}} \quad (2)$$

where $y_{N\text{-}i}$ is a vector with a zero component in place of y_i and components equal to that of y for the remaining products. Product specific returns to scale are said to be increasing decreasing or constant as $S_i(y)$ is greater than, less than, or equal to one respectively.

Economies of scope refer to efficiencies that arise from the simultaneous production of different outputs in a single firm as opposed the production of these outputs in specialized firms. The degree of economies of scope at output vector y relative to product set T is defined as:

$$SC_T(y) \equiv \frac{[C(y_T) + C(y_{N-T}) - C(y)]}{C(y)} \quad (3)$$

where fragmentation of the firm increases, decreases or leaves total costs unchanged as SC_T is greater than, less than, or equal to zero respectively.

Though the conventional method of testing for scope economies allows us to calculate the degree of scope economies across aggregated output measures, the possibility may still exist that within an output category there are economies of scope. For example, if we aggregate two outputs into one aggregated output category, though these outputs may be similar in their resource requirements, the marginal cost of producing an additional amount of the aggregated output may change depending on the scope of the products contained in this output category. If there is some degree of complimentarity between these two outputs, a firm producing both of these outputs in equal numbers within an aggregated output category may experience lower costs for a given amount of this aggregated output than a firm producing an equivalent amount of this aggregated output but lacking within-category diversity. To account for this possibility, we define total output for aggregated category Ω as:

$$Y_\Omega = \left[\sum_{\omega \in \Omega} (Y_\omega)^\rho \right]^{1/\rho}$$

where Y_Ω corresponds to a firm's output of aggregated good Ω and Y_ω is the output of an individual good which is included in the set Ω. Estimating the value of ρ in the above equation will indicate the degree of within-category scope economies. Given the structure of this functional form, a value of $\rho>1$ indicates diseconomies of scope, while a value of $\rho<1$ indicates economies of scope.

4. Construction of an Output Index

The construction of our output index employs the gross revenue for each inpatient discharge which is used as a proxy for the amount of care consumed by a patient in a given hospital. Total charges (gross revenue) are included for each discharge in our sample (see data section for details) and because the charges in our data are constructed off of a uniform charge list which is identical for each patient within a hospital, this gross revenue figure is related to the amount of care consumed by a patient for a given hospital stay. Thus it more closely reflects the amount of care consumed than does a patient day or hospital discharge. The following section details the means by which we exploit these charges to construct a quantity measure for each discharge in the dataset. In it, we detail the assumptions we make regarding the relationship of these charges to quantity of care consumed, as well as the estimation procedure used to construct the output index.

Suppose hospital j produces N outputs using a production technology which can be represented by the cost function

$$C_j(Y_{1,} Y_2, \ldots, Y_N).$$

Let each hospital j's gross charges consist of a markup over marginal cost, regardless of the output produced and a marginal cost which varies across outputs. Furthermore, assume that each consumer, i, consuming output type n consumes a quantity invariant to the hospital at which she receives care. The gross revenue for a given discharge from hospital j can thus be expressed as:

$$R_{ijn} = \gamma_j \frac{\partial C_j}{\partial Y_n} y_{in} \tag{4}$$

where

$$\gamma_j = \text{ a markup over marginal cost for hospital } j$$

$$\frac{\partial C_j}{\partial Y_n} = \text{marginal cost for output type } n \text{ at hospital } j$$

y_{in} = quantity of output type *n* consumed by person *i*.

Taking logs,

$$\ln(R_{ijn}) = \ln(\gamma_j) + \ln\left(\frac{\partial C_j}{\partial Y_n}\right) + \ln(y_{in}). \qquad (5)$$

Allowing $y_{in} = \exp(X_{in}\beta_n + v_{in})$ our estimating equation will be:

$$\ln(R_{ijn}) = \alpha_{jn} + X_{in}B_n + v_{in} \qquad (6)$$

where α_{jn} is a hospital specific scaling factor for caretype *n* which encompasses both the hospital specific markup and marginal cost, X_{in} is a vector of observable consumer diagnostic and demographic characteristics, β_n is a vector of coefficients for these characteristics and υ_{in} denote unobserved patient characteristics. Note that this representation provides us with the flexibility for marginal cost to vary between outputs for a given hospital. A regression of the log of gross charges on a full set of hospital dummies and a set of patient characteristics (such as diagnosis and demographic characteristics) enables recovery of $\hat{\alpha}_{jn}$ for each hospital which represents the average hospital scaling factor for a particular hospital-output type pair and $\hat{\beta}_n$ which represent the weights assigned to the characteristics for each individual patient consuming output *n*. Using these estimates, the log quantity for each patient (scaled in terms of hospital *j*) can be written as

$$\ln(y_{ijn}) = \hat{\alpha}_{jn} + X_{in}\hat{\beta}_n + \hat{v}_{in}. \qquad (7)$$

Because hospitals may vary in their scaling factor, we construct a normalization corresponding to an "average" consumer across the sample by utilizing the estimated coefficients and setting all diagnosis and demographic characteristics at their sample means, $\overline{X}_n$. The quantity for this average consumer scaled in terms of hospital *j*, can be written as $\ln(y_{jn}) = \hat{\alpha}_{jn} + \overline{X}_n \hat{\beta}_n$. We rewrite (7) as separate components corresponding to the normalized hospital-scaled quantity and the common scaled quantity which is hospital invariant,

$$\ln(y_{ijn}) = (\hat{\alpha}_{jn} + \overline{X}_n \hat{\beta}_n) + (X_{in}\hat{\beta}_n - \overline{X}_n \hat{\beta}_n) + \hat{v}_{in}. \quad (8)$$

Taking exponents, an estimator of the quantity of care type *n* that person *i* consumes at hospital *j*, $\hat{y}_{ijn}$, based on person *i*'s observable characteristics can be written as:

$$\hat{y}_{ijn} = K * \exp(\hat{\alpha}_{jn} + \overline{X}_n \hat{\beta}_n)\exp(X_{in}\hat{\beta}_n - \overline{X}_n \hat{\beta}_n) \quad (9)$$

where *K* is Duan's (1983) smearing estimator.[2]

The hospital-invariant quantity of output type *n* consumed by person *i* can now be written as:

$$\hat{y}_{in} = \frac{y_{ijn}}{y_{jn}} = K * \exp(X_{in}\hat{\beta}_n - \overline{X}_n \hat{\beta}_n) \quad (10)$$

which is a function of only the patient characteristics and the characteristics of a normalized discharge. Hospital *j*'s, total quantity of output *n* can be written as

$$Y_{jn} = \sum_{i=1}^{S_n^j} \hat{y}_{in} \quad (11)$$

where S_n^j represents the number of discharges of output type *n* at hospital *j*.

[2] The smearing estimator is required to ensure that the untransformed estimates of the expected values of revenue do not suffer from transformation bias brought about by the fact that the parameters are estimated in a log-log specification.

5. Data

We use data from California's Office of Statewide Health Planning and Development (OSHPD) which maintains a variety of datasets on various aspects of health care in the state. Below we briefly describe each of the particular datasets that we draw upon and the criteria for selecting subsets of the data.

5.1 Discharge Data

All nonfederal California hospitals are required to submit specific data on every patient discharged from their facility including information on patient demographics, diagnostic and treatment information, payment source and total charges. These data are reported for the full calendar year and include detailed patient information including on age, race, sex, and county of residence as well as diagnosis characteristics. A number of patient demographic characteristics are masked in the data while other sensitive items such as age are entered categorically. These data also contain charges based on hospital's full established rates. Although these charges are a poor proxy for actual price paid, they are calculated as the product of the services provided multiplied by a price contained in a uniform charge master list for each hospital and are thus related to the amount of care consumed by a patient.

5.2 Financial Data

The submission of an annual financial report including a detailed income statement, balance sheet, statements of revenue and expense, and supporting schedules, as well as a quarterly hospital financial report is required of all California hospitals. These financial reports are based on a uniform accounting and reporting system developed and maintained by the OSHPD. The annual financial data correspond to hospital fiscal years which are not necessarily synchronized with calendar years while the quarterly data are synchronized with both calendar years and each other. The annual data contain variables useful to the construction of input prices such as hourly wages, hours, benefits and data on the hospital physical plant. These items are likely not to be sensitive to synchronization and are thus used in the construction of input prices. There is also information on ownership and teaching status in these data. The quarterly data contain items such as outpatient visits and total operating expenses which require synchronization with the discharge data in order to accurately estimate the relationship between hospital output and cost. For these items, we sum the quarterly data up to annual levels and use this in the construction of our total cost and outpatient visit variables.

5.3 Selections and Variable Construction

For 2003, there are over 3.9 million discharges in the data. Because we require a value of hospital charges in the construction of our output index, we eliminate Kaiser hospitals which are members of a vertically integrated organization and thus do not report charges. We also eliminate Shriner's hospitals which do not charge their patients. Because our universe is short-term general hospitals, we eliminate children's hospitals, and hospitals specializing in psychiatric, chemical dependency or long-term care. After all exclusions, we are left with 3,470,880 from 320 hospitals.

For the construction of both our input prices and capital variables, we employ the financial data which separate out the average hourly wage at each hospital by type of labor. To calculate input prices for each type of labor we first multiply the hourly wage by the total number of hours (both productive and non productive) worked for each labor type. Because benefits also account for a substantial portion of compensation, we allocate a portion of total benefits to each labor type based on the total number of hours worked. Our share data is calculated using this amount of total compensation for each type of labor divided by the total cost (see below).[3] Using this measure we divide by the total number of hours worked to get the input price by labor type at each hospital.

Construction of capital prices and quantities in cost function estimation is notoriously difficult [Folland et. al. (1997)]. We construct an economic measure based on construction costs for hospitals in California in 2003. We start with the total square feet present at a hospital, available in the OSHPD financial data. Meade and Kulick (2007) conclude that the cost for a fully furnished hospital building in 2006 is approximately $1000 per square foot. Because hospital costs have increased at a rate larger than that of inflation, we deflate this to a 2003 cost using a cost hospital cost deflator specified in a Davis Langdon report commissioned by the California Hospital Association.[4] Using these two measures, we now have an approximation to the total dollar amount of the amount of capital possessed by each hospital. To construct the price for this capital, we employ the average interest rate for corporate industrial bonds and municipal bonds as reported from the Mergent Bond Record for 2003. Not-for-profit hospitals are assigned the municipal bond interest rate due to their tax-exempt status while for-profits are assigned the industrial rate.

For our measure of cost, we use the sum of total operating expenses as reported by the quarterly data. Because a portion of these expenses contain capital related items,

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[3] For hospitals reporting data for only part of a year, we scale the share number up by [12/(# of months reporting)] while leaving the hourly measure unchanged.

[4] See http://www.calhealth.org/public/press/Article%5C103%5CConstruction%20Cost%20Escalation%20in%20CA%20January%202006%20no%20cover%20letter.pdf.

we subtract out minus depreciation, rental and interest expense. Using this measure, we then add back the capital expense as computed above.

We classify inpatient discharges into three different categories: primary care, secondary care, tertiary care. This is done using a ranking system that classifies DRGs according to the resource requirements for each type of care. Our ranking methodology is as follows:

1) Rank DRGs by the number of hospitals having at least 1 case. Fewer hospitals indicate a higher rank.

2) Rank DRGs by the percentage of urban hospital service that is provided to residents in non-urban areas. Higher percentages indicate a higher rank.[5]

3) Rank DRGs by the typical Resource Intensity Weight Value as recorded by the Centers For Medicare and Medicaid Services (CMS). Higher resource intensity indicates a higher rank.

4) Rank DRGs by the percentage of procedures of this type performed in a teaching hospital. A higher percentage corresponds to a higher rank.

We then sum these ranks across each DRG and calculate a rank based upon this number. Starting with the highest ranked DRG we count the number of discharges with the highest rank which account for 10% of the discharges in the sample. These are classified as tertiary DRGs. The DRGs accounting for the next 40% of discharges are classified as secondary DRGs, while the DRGs accounting for the lowest 50% are classified as primary. Table 1 contains information of the characteristics on individuals in each category.

[5] We the county level Urban-Rural Classification Scheme developed by the National Center for Health Statistics.

[INSERT TABLE 1 ABOUT HERE]

6. Estimation

6.1 Output Index

Estimation of the output index requires the estimation of 3 separate regressions, one for each output type contained in the discharge data. Each regression contains dummies for each hospital as well as dummies for DRG, sex, race, number of other procedures, number of other diagnoses, as well as a dummy for whether the visit was scheduled or unscheduled.[6] Descriptive statistics for these regressions are contained in table 2.

[INSERT TABLE 2 ABOUT HERE]

Using the output index estimate for a normalized primary discharge, outpatient quantities are constructed by dividing the total outpatient revenue for a hospital by the total number of outpatient visits in that hospital. Using this average revenue amount per visit, we divide by the normalized hospital-specific primary care revenue amount, and assume that all outpatient visits within a hospital consume the same quantity of care and that the difference in the revenue per outpatient visit differs from that of a primary care discharge solely due to the difference in quantity consumed. Multiplying this number by the number of outpatient visits gives the quantity of outpatient care. Table 3 presents descriptive statistics over hospitals for both the output index as well as by the number of discharges.

[INSERT TABLE 3 ABOUT HERE]

6.2 Cost Function

[6] As mentioned in our data section, a number of characteristics are masked. Masked observations were coded as "unknown" in our regression.

Table 3 contains descriptions of the variables used in our translog cost function. The equation to be estimated is written as:

$$\log C(Y,w) = \alpha_o + \sum_{i=1}^{N} \alpha_i \log Y_i + \sum_{j=1}^{M} \beta_j \log w_j + \tfrac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N} \delta_{ik} \log Y_i \log Y_k$$
$$+ \tfrac{1}{2}\sum_{j=1}^{M}\sum_{k=1}^{M} \gamma_{jk} \log w_j \log w_k + \sum_{i=1}^{N}\sum_{j=1}^{M} \rho_{ij} \log Y_i \log w_j + \beta_{FP} FP + \beta_{TEACH} TEACH + \varepsilon \qquad (12)$$

while the restrictions:

$$\sum_{i=1}^{N} \alpha_i = 1, \quad \sum_{j=1}^{M} \gamma_{jk} = \sum_{k=1}^{M} \gamma_{jk} = \sum_{j=1}^{M} \rho_{ij}$$

imposed to ensure homogeneity of degree one in input prices as required by economic theory. Additionally, because cost is often hypothesized to be linked to ownership status, we include an indicator variable for whether the hospital is owned by a for-profit entity. Furthermore, because teaching hospitals may have higher costs due to their engagement in educational and training activities, we include an indicator variable for hospital teaching status.[7]

While estimation of the translog could be done directly, gains in efficiency can be realized by estimating optimal, cost minimizing input demand equations which can be obtained by logarithmically differentiating the cost function with respect to each input price to yield (for *i*=1,….8 inputs):

$$\frac{\partial \log C}{\partial \log w_i} = \frac{w_i}{C} \cdot \frac{\partial C}{\partial w_j} = \frac{w_i X_i}{C} = \alpha_i + \sum_{j=1}^{M} \log w_j + \sum_{i=1}^{N} \rho_{ij} \log Y_i + \varepsilon_i \qquad (13)$$

[7] Note that this could also be interpreted as corresponding to an omitted output, however, the treatment of teaching status as such would preclude estimation due to the presence of only 25 teaching hospitals and the inability of the translog functional form to accommodate output values of zero.

where the second equality follows from Sheppard's Lemma and ε_i is a disturbance term for the i^{th} input equation. Because cost shares sum to unity, only 7 input share equations are independent. Thus one input demand equation must be deleted from the system. We choose the category "supplies and equipment" which we cannot observe in our data. Assuming the nine equations have disturbances that are distributed multivariate normal with mean zero and a constant covariance matrix, we can estimate this system of equations using the iterative Zellner efficient estimation procedure. This procedure is asymptotically equivalent to maximum likelihood which due to our deletion of an input share equation is necessitated to ensure invariance of the estimated parameters. The consequent parameter estimates for the deleted input can be recovered from the homogeneity restrictions in (12).

Within this framework, as Berndt (1991) notes, the random disturbance terms in the input share equations are interpreted as random errors that firms make in choosing their cost-minimizing input bundles. McElroy (1987) proposes the use of a general error model in which the error specification is embedded in the optimization model due to differences in firm practices unknown to the econometrician. However, Berndt's discussion of McElroy's method notes that a study by Norsworthy (1990) finds parameter identification of such models is problematic without the imposition of constant returns to scale, an obviously unattractive assumption given the purposes of this study.[8]

7. Results

[INSERT TABLE 4 ABOUT HERE]

[8] I rely on Berndt's characterization of Norsworthy's results due to the fact that I could not locate the Norsworthy article at the time that this draft was written.

The regression results using our sample of 320 hospitals are reported in table 4. In general, the estimation produces sensible results. The estimated mean cost share intercepts associated with each wage type are positive and highly significant. Summation of these estimated shares at the mean indicates that registered nurses account for the largest share of hospital labor expense, followed by technical and specialist labor, clerical labor, management, and licensed vocational nurses. Capital accounts for approximately 10% of long run hospital expenses, while equipment and supplies constitute around 45%.[9] Though our total labor share may seem lower than in hospital cost studies employing a short run function, this is due to the fact that these studies take into account short run costs only and thus omit capital's share from total costs. Our input share estimates are roughly consistent with the input share estimates of Keeler and Ying (1996) who find labor's share equal to approximately 45%, though our capital share is lower than their estimate. Also, our for-profit and teaching variables indicate that for-profit hospitals do not have significantly lower costs on average than do not-for-profit and government hospitals and that teaching hospitals do have higher costs.

[INSERT TABLE 5 ABOUT HERE]

The own price elasticities with respect to each input type are presented in table 5. All point estimates of these elasticities are negative as would be expected. However, the own price elasticities with respect to Registered Nurses, LVNs Aides and Orderlies are not different from zero at the 5% level.

The first order coefficients on our outputs correspond to the output elasticities at the mean of the sample. All measures are positive and significant at the 1% level. Using

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[9] It should be noted that as a robustness test we estimated out cost function at interests rates ranging from 1.5% less than our employed interest rate through 7% more than our employed interest rate and found only minor changes in the magnitude of scale and scope economies estimated by our function.

these measures, we can calculate marginal costs for each type of output using the formula:

$$\frac{\partial C}{\partial Y_i} = \frac{\partial \log C}{\partial \log Y_i} \cdot \frac{C}{Y_i} \tag{14}$$

Because marginal cost at the mean is denoted in units of the output index, in order to convert this marginal cost calculation into a cost per discharge, we scale up marginal cost by the average quantity weight per discharge for each type of care. Marginal cost estimates per discharge are presented in table 6. The marginal cost for a tertiary discharge is around $24,000, for a secondary discharge is $8,100, for a primary discharge is $4,300 and for an outpatient visit is $207.

[INSERT TABLE 6 ABOUT HERE]

The subsequent sections of our analysis utilize calculations which require the use of the parameters of the cost function to investigate both the properties of the cost surface as well as simulate mergers of hospitals. Thus significant departure of our cost function from actual costs along specific portions of the cost surface may invalidate any possible useful inference one could make using these estimates. Furthermore, as Vita (1990) points out, parametric cost functions can perform poorly at points distant from the means of the data. Table 7 presents predicted costs versus actual costs for six groups of hospitals based on the number of staffed beds at each hospital. The estimated function appears to overestimate actual costs in hospitals with less than 145 beds and underestimate actual costs in hospitals with 145 or more beds. The extent of this overestimation worsens as the hospital size increases, and in the largest category (305-875 beds) the function underestimates cost by nearly 7%.

7.1 Scale Economies

The degree of scale economies is calculated using the measure given in equation (1). Table 8 presents scale economies at output levels corresponding to the mean output vector (row 1) as well as output vectors corresponding output levels 25% and 50% larger than the mean (rows 2 and 3). Equating these numbers to bed size, row 1 would correspond to a hospital with approximately 183 beds, row 2 corresponds to a hospital with approximately 220 beds while row 3 corresponds to a 258 bed hospital.

[INSERT TABLE 8 ABOUT HERE]

At the mean output level, the estimates indicate increasing returns to scale. The point estimate of 1.16 implies that a 1% increase in all four types of care for the average hospital would lead to a 0.86% increase in costs for this hospital. Furthermore, this measure of scale economies is significantly different from 1 (the constant returns to scale threshold) at the 5% level. The point estimate continues to indicate economies of scale at the second output vector although the hypothesis of constant and decreasing returns to scale cannot be rejected. The point estimate of scale economies at the third output vector indicates decreasing returns to scale, however, the hypothesis of constant or even increasing returns to scale cannot be rejected at this output vector. In fact, the scale measure becomes significantly different from 1 at an output vector corresponding to 16,475 discharges or approximately 277 beds.

Using the definition for product specific scale economies given in (2), we can calculate point estimates of product specific returns to scale for each output category. We modify the definition given in (2) and replace a small positive value, ε_i (equal to the 25th percentile of product *i*) in place of y_i and substitute y_i-ε_i into the denominator to enable the use of this measure with our translog function. Table 9 lists the estimated measures of product specific scale economies for each measure of output at the mean output level for each output type. For example, an entry of 1.27 in table 9 for primary care indicates that a hospital with 5,129 discharges (about 183 beds) would experience a 0.79% increase in costs for a 1% increase in primary care holding constant the output of all other care types at their mean values.

[INSERT TABLE 9 ABOUT HERE]

[INSERT FIGURE 1 ABOUT HERE]

Primary, secondary and tertiary care all show increasing returns to scale at the mean output value while outpatient care exhibits decreasing returns to scale. A plot of product specific returns to scale for each output type is included in figure 1. The plots indicate that scale economies are exhausted for tertiary care at approximately 1,423 tertiary discharges (216 beds), while scale economies for secondary care and primary care are exhausted at 4,589 secondary discharges (204 beds) and 5,898 discharges (203 beds) respectively. Finally, outpatient care exhausts returns to scale at around 89,000 visits.

7.2 Scope Economies

Using the definition for economies of scope given in (3), we can calculate point estimates of scope economies for each output combination. However, we modify this definition to accommodate our functional form by defining an output vector $\mu = (\mu_1, \mu_2, \mu_3, \mu_4)$ and defining the degree of 2, 3 and 4 product scope economies as follows:

$$SC_2(y) = \frac{C(Y_1 - \mu_1, \mu_2, \frac{\mu_3}{2}, \frac{\mu_4}{2}) + C(\mu_1, Y_2 - \mu_2, \frac{\mu_3}{2}, \frac{\mu_4}{2}) - C(Y_{1,} Y_2, \mu_3, \mu_4)}{C(Y_{1,} Y_2, Y_3, Y_4)} \qquad (15)$$

$$SC_3(y) = \frac{C(Y_1 - \mu_1, \frac{\mu_2}{2}, \frac{\mu_3}{2}, \frac{\mu_4}{3}) + C(\frac{\mu_1}{2}, Y_2 - \mu_2, \frac{\mu_3}{2}, \frac{\mu_4}{3}) + C(\frac{\mu_1}{2}, \frac{\mu_2}{2}, Y_3 - \mu_3, \frac{\mu_4}{3}) - C(Y_{1,} Y_2, Y_3, \mu_4)}{C(Y_{1,} Y_2, Y_3, Y_4)}$$

$$SC_4(y) = \frac{C(Y_1 - \mu_1, \frac{\mu_2}{3}, \frac{\mu_3}{3}, \frac{\mu_4}{3}) + C(\frac{\mu_1}{3}, Y_2 - \mu_2, \frac{\mu_3}{3}, \frac{\mu_4}{3}) + C(\frac{\mu_1}{3}, \frac{\mu_2}{3}, Y_3 - \mu_3, \frac{\mu_4}{3}) + C(\frac{\mu_1}{3}, \frac{\mu_2}{3}, \frac{\mu_3}{3}, Y_4 - \varepsilon_4) - C(Y_{1,} Y_2, Y_3, Y_4)}{C(Y_{1,} Y_2, Y_3, Y_4)}$$

These definitions are similar to that used by Preyra (2006) and are constructed to ensure that the sum of the μ parameters are differenced out in the "specialized" cost functions so as to prevent bias favoring conclusions of economies of scope.

[INSERT TABLE 10 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

Table 10 presents estimates of scope economies evaluated at the mean output vector. An entry of 0.21 in table 10 for the tertiary/secondary measure indicates that a 183 bed hospital producing the mean quantities of 989 tertiary discharges and 3,990 secondary discharges together produce these quantities at a 21% savings than two hospitals that produced these exact quantities at facilities that were (nearly) specialized. Figure 2 shows economies of scope for all product sets. While the point estimates in table 10 show economies of scope between all types of care, as figure 2 indicates, economies of scope are exhausted between most product combinations between 1.6 and 2.6 times the mean output vectors. Notable exceptions to this, however, are the tertiary/outpatient and secondary/primary scope measures. Due to the negative and significant interaction terms between these outputs in our estimated cost function, the plots indicate economies of scope everywhere between these two output types. [10]

Finally, as we detail in Section 3.3, the estimates of scope economies using traditional measures do not account for the possibility of scope economies existing within output categories. To account for this possibility, we first classify the total output produced in each output category by the Major Diagnostic Category (MDC) corresponding to each discharge. There are 25 MDC's, each of which corresponds to a single organ system. For each hospital *j* and output type *n* we embed a CES function of the form:

$$Y_{jn} = \left[\sum_{d=1}^{25} (Y_{jnd})^{\rho} \right]^{1/\rho}$$

where Y_{jnd} corresponds to hospital *j*'s output of MDC *d* which is classified as caretype *n*. Given the structure of this functional form detailed in Section 3.3, a value of $\rho>1$ indicates diseconomies of scope, while a value of $\rho<1$ indicates economies of scope. We then re-estimate our cost function using a grid search algorithm to estimate one ρ parameter which extends across all inpatient output types.[11] Our estimated parameter of .58 indicates the presence of within category scope economies.

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[10] These results should, however be viewed with caution. An alternative test for scope economies between product pairs, referred to as the weak cost complementarities test, defines a sufficient condition for the presence of scope economies between product i and product j as:

$$\frac{\partial C}{\partial y_i \partial y_j} < 0 .$$

The calculation of the weak cost complementarities measure for the tertiary/outpatient and secondary/primary categories indicate values of -.042 and -.06 respectively, however, the standard errors on these estimates of .04 and .06 imply that they are not significantly different from zero at conventional levels.

[11] The algorithm proceeds by first calculating the value of output for each category for a given ρ. The cost function is then estimated using the calculated value of output in each category and the R^2 is recorded for this estimation. This is repeated for every parameter in the grid. The ρ corresponding to the highest R^2 is the reported value of ρ.

7.3 Relative Performance of Output Index

In order to examine the implications of defining output using our output index and output classification categories, we re-estimated our cost function output measures commonly employed in previous hospital cost function studies. Specifically, we classify output using only inpatient and outpatient as our classification categories and define output using a discharge count in one specification and patient days in another while appending a case-mix variable onto each specification.[12] Figure 3 plots point estimates of scale economies using each output measure.

[INSERT FIGURE 3 ABOUT HERE]

Point estimates from the output index indicate that scale economies are exhausted around 13,140 discharges or 228 beds. The functions estimated using discharges and patient days as the unit of output indicate the exhaustion of scale economies around 12,534 and 9,603 discharges or 219 and 175 beds respectively. Using these point estimates, the output index indicates that minimum efficient scale is reached at a level that is at an output level 4% greater than would be indicated using discharges and an output level 30% greater than would be indicated using patient days.

Because we depart from previous output measurement methods in two different dimensions (classification and measurement), we assess whether the output index produces a different measure of economies of scale at the mean output vector and whether these differences are due to our use of the output index or merely due to our more theoretically appropriate classification of output. Table 11 shows estimates of scale economies using all three measures of output evaluated at the mean output vector.

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[12] Because we were only able to obtain case-mix indices for 305 of our 320 hospitals, these tests were run on the smaller sample for all specifications to ensure consistency.

[INSERT TABLE 11 ABOUT HERE]

To assess whether the differences in scale economies using the output index are significant, we generated bootstrapped standard errors for each scale measure. Using these standard errors we can conclude, using the numbers in the third row for example, that when employing our four output classification system and output index, economies of scale at the mean output vector are estimated to be 1.11 while using patient days and a two output classification system produces an estimate of 0.98 for a difference of 0.135. Using the bootstrapped standard errors we can conclude that this difference is significant at the 5% level and thus the measure of scale obtained using our cost function is significantly greater than that obtained using a previously used output definition and classification technique.

Using patient days in the specification, the output index appears to produce differences that are significant at the 10% level when using the two-output classification scheme. However, once output is classified into four categories, this difference disappears and the scale estimates are virtually identical. Using discharges as an output measure has no significant effect on the scale measure and in some cases, a simple counting of discharges produces measures of scale that are greater than those using the output index. From this table, it seems that theoretically consistent output classification is adequate for accurate estimates of economies of scale and the additional theoretical refinements embodied in the output index do little to our estimates of scale economies.

8. Policy Applications

The parameters of the estimated cost function can be used to gain insight into a number of health policy issues. In the following section, we make use of our cost function to analyze a set of hypothetical consolidations between hospitals in our data. We also construct estimates of marginal cost by diagnosis category and combine this with data on Medicare reimbursement rates in order to determine whether these reimbursement rates cover the marginal cost of care at the average hospital.

8.1 Merger Simulations

The role of efficiencies in merger analysis has received an increasing deal of attention from commentators and government agencies concerned about the need to protect the competitive strength of the health care industry. The claim that the wave of mergers in the health care industry was driven by the need to reduce excess capacity and generate substantial efficiencies that will benefit health care consumers has become increasingly important in decisions made by the antitrust agencies, as well as in the cases tried by these agencies. [ABA Handbook (2003)]. The use of efficiency defenses in hospital mergers has been employed in some form in six of the litigated merger cases tried since 1990, and the courts have increasingly recognized a role for efficiencies in merger analysis, a transition which has occurred largely in the context of hospital merger litigation. The acknowledgment of such efficiencies has been relied upon by the FTC to the extent that in 1999 former FTC chairman Robert Pitofsky stated "significant efficiencies can be achieved through a merger, and the Commission has relied on such efficiencies in recommending that some mergers *not* be challenged."[13]

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[13] *See* Robert Pitofsky, *Efficiencies in Defense of Mergers: Two Years After,* 7 Geo. Mason Law Review. 485 (1999)

Using the estimated cost function, we simulate mergers of 3 hospital pairs included in our data. The first merger that we consider is between two public, semi-rural hospitals, Palm Drive Hospital and Mendocino Coast District Hospital, each with around 50 beds. Each provides mainly primary, secondary and outpatient care with a small amount of tertiary care with the output of each type of care falling well below our sample mean. The second merger we consider combines two non-profit hospitals in Los Angeles, St. Luke's Hospital and St. Francis Memorial Hospital, one of which maintains 209 beds and the other of which maintains 170 beds. We consider this merger due to the fact that with the exception of outpatient care, each hospital contains a vector less than that of our sample mean, while the combined entity will contain an output vector that greater than the mean quantities in our data. The third merger is between Coalinga Regional Medical Center and Corcoran District Hospital hospitals which provide mostly primary and outpatient care and a very small amount of tertiary care.

[INSERT TABLE 12 ABOUT HERE]

Using estimates from our cost function, the merger Palm Drive and Mendocino Coast would decrease total costs from around $65.6 million to $57.7 million, a savings of nearly 12%. For the hospitals considered in our second merger, our function indicates that the combination of these two facilities would imply a cost savings of almost 6%, with total cost decreasing from $212 million to $198 million. Finally our merger of Coalinga and Corcoran show only a savings of around 20%, with total costs decreasing from around $24.5 million to approximately $19.6 million.

Because antitrust authorities are often concerned with the price effects that a given merger may have on consumers, we extend these merger simulations to calculate the potential for price decreases brought on by these mergers. We refer to these as potential price decreases because without an assumption on the conduct of firms, we cannot conjecture as to whether in increase in market power by the merging of these firms would outweigh any efficiencies generated by such mergers. Table 13 presents prices for each type of care at each of our six merging hospitals.

[INSERT TABLE 13 ABOUT HERE]

Our prices are calculated assuming a constant elasticity of -5.67, as calculated in Gaynor and Vogt (2002) and using the relationship $P=MC/(1+(1/\eta))$ where η is the elasticity of demand. Furthermore, we adopt the conservative approach of reporting the potential for price increases/decreases as the difference in the merged price and the lowest priced hospital of the two merging entities

Our estimates show that the two smaller mergers have the potential to reduce price for primary care by around 20%. This is not surprising given our earlier findings of the exhaustion of primary scale economies at a level of 5,898 discharges. Secondary care also shows a decreases in price for the two smaller mergers though for the merger of the larger hospitals, the price decrease is small. For tertiary care, the merger of Palm and Mendocino produces little price savings, though the St. Luke's-St. Francis merger produces a potential price decrease of nearly 11% and the Coalinga-Corcoran combination shows savings of around 17%. Finally, all mergers produce negative savings (potential price increases) for outpatient care. This is likely due to the fact that out product specific returns to scale measure for outpatient care shows decreasing returns to scale at almost all output levels.

8.2 DRG Profitability

Knowing whether hospital reimbursements cover costs is a fundamental issue in hospital finance. The failure of Medicare reimbursement to cover cost can lead to cost shifting (the phenomenon in which changes in administered prices of one payer lead to compensating changes in prices charged to other payers) or the altogether refusal to treat Medicare Patients. Because Medicare patients comprise roughly 40 percent of all hospitalized patients, reductions in Medicare payments have a significant impact on revenues for patient care services and hospitals.[14] A survey by the American Hospital Association found that two-thirds of all responding hospitals lost money on Medicare and Medicaid services in 2004 while a 2006 report by MedPAC, a federal advisory agency for Medicare, found that Medicare margins for hospitals fell from about 5 percent in 2001 to -3 percent in 2004.[15]

Given the way by which our cost function was estimated, we can construct marginal cost measures by DRG by utilizing the average weight assigned to each DRG using our output index. Using this approach, the marginal cost for DRG *k* of caretype *n* denoted MC_{kn} can be written as:

$$MC_{kn} = \frac{\sum_{i \in k} y_{in}}{K} \cdot MC_n \qquad (16)$$

where *K* is the total number of discharges of DRG type *k* and marginal costs are constructed at the mean output vector as specified in equation (14). Using these estimated measures of marginal cost combined with data on Medicare reimbursement rates, we can calculated the margin for each DRG in our data to assess the degree to which Medicare

[14] http://findarticles.com/p/articles/mi_m4149/is_3_41/ai_n16497866
[15] See http://www.minneapolisfed.org/pubs/fedgaz/07-01/reimburse.cfm.

reimbursement rates cover the marginal cost of hospital treatment at the average hospital in our sample.

Each year, Solucient Inc. publishes “The DRG Handbook”, a manual with detailed clinical, financial, and statistical data on the 100 DRGs with the most Medicare Discharges. This manual contains information on the average cost per discharge for each DRG using a methodology which applies each hospital’s cost-to-charge ratio to its actual charges, and average reimbursement rate per discharge for each DRG. Both of these measures are calculated by Solucient using the Medicare Provider and Analysis Review File released by CMS. Included for each DRG is a breakdown for each state. Using the 2005 DRG handbook (which contains cost and reimbursement measures for the 2003 calendar year) we compare our estimates of marginal cost to the measures reported for the state of California. Overall, our estimates of marginal costs are notably higher than the average cost measures reported in the DRG manual (about 20%), though the Solucient costs fall within the (albeit large) confidence intervals for these calculated marginal costs. The correlation between our point estimates of marginal cost and the reported costs in the manual is 0.98.

We incorporate the California reimbursement amounts reported in the manual to calculate a profit margin for each DRG. Our point estimates indicate a marginal profit margin of -19.5% across the 100 DRGs compared to the DRG manual’s -4.3%.[16] Table 14 presents the 10 most profitable and least profitable DRGs as calculated using our measure of marginal cost.

[INSERT TABLE 14 ABOUT HERE]

[16] The spearman rank correlation between our ranking of the most profitable DRGs and Solucient’s ranking of the most profitable DRGs (as indicated by the profit margin) is .69. A test of independence is rejected at the 1% level.

The 10 most profitable DRGs are all DRGs that we classify as involving a secondary level of care, while the 10 least profitable are all diagnoses which fall into the primary category. Additionally, these calculations indicate that of the 100 DRGs in the manual, only 4% have non-negative profit margins.

We note, however, that the Solucient measures correspond most closely to average costs rather than the marginal cost measures to which we compared them. Thus our findings of negative profitability suggest that the average hospital operates at a point on its marginal cost curve in which the Medicare reimbursement amounts no longer cover the marginal cost of most discharges. In future work, we plan to estimate the point on this marginal cost curve at which Medicare Reimbursement rates adequately cover these costs.[17]

9. Conclusion

Recent hospital merger and acquisition activity has increased the importance of knowledge about the structure of hospital costs. We contribute to the body of econometric research on the specification and estimation of hospital cost functions by developing an output index which accounts for hospital case heterogeneity while also maintaining a functional form flexible enough to allow for theoretically sound estimates of scale and scope economies. We find significant evidence of economies of scale, and limited evidence of scope economies. A comparison of our output index with previously employed output measures indicates that economies of scale are exhausted at higher levels of care, though the differences are only slight. Our research indicates that hospital

[17] In addition, there are large confidence intervals for these marginal costs. They are, in fact, large enough that we cannot rule out profitability at the average hospital for ANY of the DRGs. This is also a topic for further exploration.

case heterogeneity may not bias estimates as has been conjectured and that given proper output classification additional controls for fine levels of patient heterogeneity may be unnecessary.

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Appendix A: Functional Forms of the Cost Function

When choosing a functional form for a cost function, one must be mindful of the properties imposed on production technology and its suitability within the context of the topic being analyzed. Furthermore, one must carefully consider the tradeoffs between theoretical consistency and empirical tractability. For example, if a researcher wishes to estimate a measure of returns to scale within an industry, she must be careful not to choose a functional form which presupposes the presence of increasing or decreasing returns to scale. Additionally, a functional form may permit the perfect estimation of a given technology but require so many parameters so as to preclude statistical estimation given the available data. For the purposes of a study focusing on scale and scope economies in the hospital industry, the employed functional form must permit sufficient flexibility with regards to scale and scope economies so as to allow estimation of functional relationships which stem from the data rather than the functional form employed.

A cost function which is to allow the existence of scope economies must assume that transformation function exhibits jointness in outputs. A transformation function $\mathrm{F(X,Y)}$ is said to be non-joint if it can be portrayed as a collection of *n* single product firms, each of which has a separate production for one of the outputs, i.e.

$$
\begin{aligned}
Y_1 &= f^1(X_1^1,\dots,X_m^1) \\
Y_2 &= f^2(X_1^2,\dots,X_m^2) \\
&\dots\dots\dots \\
Y_n &= f^n(X_1^n,\dots,X_m^n)
\end{aligned}
$$

When the transformation function is non-joint, the cost function can be written as:

$$C(Y,w) = C^{(1)}(Y_1, w_1,\dots., w_m) + C^{(2)}(Y_2, w_1,\dots., w_m) + \dots + C^{(n)}(Y_n, w_1,\dots., w_m)$$

and thus the total cost of is the sum of producing each output separately. Because economies of scope exist if and only if production is joint[18], the use of any functional form which presupposes non-jointness will preclude the estimation of economies of scope for hospitals. By this criteria, a linear cost function of the form

$$C = \sum_i a_i y_i$$

would be unsuitable for our purposes. Furthermore, although estimation of a CES cost function,

$$C = \left[\sum_i a_i y_i^{b_i} \right]^\rho$$

allows for economies of scope, as Baumol, Panzar and Willig (1988) assert, complementarity (and thus economies of scope) must hold between each and every pair of outputs if $\rho>1$ and none of them if $\rho<1$.[19] Thus conclusions of economies or diseconomies of scope between any subset of output categories are precluded by the use of such a form.

The degree of returns to scale is dependent upon the degree of homogeneity of the production function. If the production function is homogeneous of degree α, this implies that the cost function is homogeneous of degree $1/\alpha$, with a value of $\alpha>1$ indicating increasing returns to scale and a value of $\alpha<1$ indicating decreasing returns to scale. Using this criteria, the estimation of scale economies disqualifies the use of Hall's (1973) Generalized Linear-Generalized Leontief cost function,

[18] In the case of a short run cost function, scope economies may still exist even if the production is non-joint. Because we estimate a long-run cost function, jointness is a necessary condition for the presence of scope economies.

[19] In the case of a short run cost function, scope economies may still exist even if $\rho>1$. Again this is irrelevant to our case because we estimate a long-run cost function.

$$C(Y,w) = \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{N}\sum_{l=1}^{N} a_{ijkl}\sqrt{Y_k Y_l}\sqrt{w_k w_l}$$

which is homogeneous of degree one, thereby imposing constant returns to scale.[20]

In an industry with significant variation in input prices across firms (such as the hospital industry), a suitable functional form must possess the ability to accurately portray these effects. The generalized quadratic cost function,

$$C(Y,w) = g(w)\cdot\left[\alpha_0 + \sum_i \alpha_i Y_i + \tfrac{1}{2}\sum_i\sum_j \alpha_{ij} Y_i Y_j\right]$$

is discussed in Baumol et. al. as possessing a number of favorable properties in its ability to flexibly portray a variety of output properties, while Röller (1990) shows that when g(*w*) is specified as a CES function, is sufficiently flexible to represent economies of scope or scale in the output space. It's main drawback, however, is its imposition of strong separability in outputs and input prices which restrict potentially important input price-output interactions.

For our purposes we employ the multiproduct transcendental logarithmic (translog) cost function the exact form of which is included in section 6.2. The translog function is quadratic in logarithms and is one of the family of second-order Taylor-series approximations to an arbitrary cost function. It is sufficiently flexible to allow for scope and scale economies and remains consistent with functional properties required by economic theory. The translog is by no means perfect; it has no finite representation if

[20] Li and Rosenman (2001) propose a Generalized Leontieff Function which allows for sufficient flexibility to permit estimation of returns to scale. Their proposed function, however, is rather excessive in terms of the number of parameters requiring the estimation of 232 parameters for our 8 inputs and 4 outputs.

any output is zero.[21] Chambers (1988) also notes that the translog's accuracy varies with respect to its technological approximation properties.[22] Guilkey, Lovell and Sickel's (1983) comparison of functional forms, however, concludes that "the translog form provides a dependable approximation to reality provided that reality is not too complex" while Stern (1994) describes the translog estimates as "reasonably accurate" for data in which no explicit production or cost function is specified. Furthermore, the translog function's ability to incorporate the theoretical properties required of a cost function, along with the relatively few a priori restrictions on the underlying structure of production have made it a most suitable specification for our study.

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[21] Caves, Christensen and Tretheway (1980) propose the transformation of outputs using a Box-Cox metric to ameliorate this problem. Preyra (1998), however, shows that this transformation will bias estimates of scope economies.

[22] p. 179

Table 1. Descriptive Statistics-Individuals

Variable		Sample Mean	Tertiary Sample Mean	Secondary Sample Mean	Primary Sample Mean
Total Discharges		3,470,880	360,284	1,383,253	1,727,343
Age					
	Under 1 Year	514,534	21,912	138,558	354,064
	1-17 Years	156,642	35,542	94,226	26,874
	18-34 Years	605,915	25,218	169,431	411,266
	35-64 Years	964,299	129,909	433,753	400,637
	65+	1,008,169	105,242	457,109	445,818
	Unknown	221,321	42,461	90,176	88,684
Sex					
	Male	1,131,794	144,593	478,524	508,677
	Female	1,746,352	108,894	651,416	986,042
	Other/Unknown	592,734	106,797	253,313	232,624
Race					
	White	1,995,908	180,259	793,798	1,021,851
	Black	171,204	12,500	70,393	88,311
	Other/Unknown	1,303,768	167,525	519,062	617,181
Type of Admission					
	Scheduled	753,754	172,716	375,569	205,469
	Unscheduled	2,236,716	173,936	907,454	1,155,326
	Infant	475,116	13,273	97,770	364,073
	Unknown	5,294	359	2,460	2,475
Number of Other Diagnoses		4.4	5.3	5.0	3.7
Number of Other Procedures		0.9	2.9	1.0	0.4

Table 2. Output Index Regressions

Regression	Number of DRGs	Number of Discharges	Number of RHS variables	R^2	Average quantity	Std. Dev.	Min	Max
Primary	62	1,727,343	515	0.75	1.61	1.36	0.23	75.28
Secondary	270	1,383,253	723	0.66	1.76	2.09	0.16	84.75
Tertiary	176	360,284	620	0.73	1.78	2.28	0.08	46.88

Table 3. Hospital Descriptive Statistics (N=320)

Variable		Sample Mean	Standard Deviation	Min	Max
Cost (in thousands)		130,570	149,255	3,973	1,121,537
Inpatient Discharges					
	Primary	5,129	4,032	2	23,305
	Secondary	3,990	3,464	25	21,198
	Tertiary	989	1,443	1	9,359
Outpatient Visits		122,348	148,783	2,993	1,331,526
Inpatient Quantity					
	Primary (Y_1)	8,246	6,071	5	34,990
	Secondary (Y_2)	7,035	6,334	20	39,359
	Tertiary (Y_3)	1,761	2,638	0.4	19,227
Outpatient Quantity	(Y_4)	12,897	12,738	337	97,161
Hourly Wages					
	Management (w_1)	44.69	9.30	8.34	75.35
	Technical and Specialist (w_2)	33.60	7.22	8.39	54.17
	Registered Nurse (w_3)	42.49	8.74	17.29	70.29
	Licenced Vocational Nurse (w_4)	28.62	6.16	16.32	48.01
	Aides and Orderlies (w_5)	21.82	6.04	7.23	42.73
	Clerical and Administrative (w_6)	22.84	5.83	8.29	41.40
Capital Price (Per Bed)	(w_7)	67,018	32,132	15,955	217,482

Table 4

Equation/Dependent Variable	RMSE	R^2
Total Cost	0.245	0.947
Management Share	0.020	0.284
Technical and Specialist Share	0.026	0.263
Registered Nurse Share	0.038	0.355
Licenced Vocational Nurse Share	0.011	0.408
Aides and Orderlies Share	0.020	0.233
Clerical Share	0.020	0.219
Capital Share	0.032	0.432

Parameter Estimates

Parameter	Estimate	Std. Error	Parameter	Estimate	Std. Error
Intercept	11.69674 *	0.02456	RN*SUP	-0.06873 *	0.01175
Tertiary (TER)	0.19798 *	0.03195	RN*CAP	-0.00760	0.00464
Secondary (SEC)	0.26890 *	0.07179	LVN*AO	-0.00420	0.00660
Primary (PRIM)	0.18369 *	0.04968	LVN*CL	-0.00788	0.00682
Outpatient (OUT)	0.21055 *	0.04099	LVN*SUP	0.01079 *	0.00382
1/2*TER^2	0.02316	0.03321	LVN*CAP	-0.00552 *	0.00150
1/2*SEC^2	0.06430	0.06598	AO*CL	-0.01123	0.00938
1/2*PRIM^2	0.03766 ***	0.02225	AO*SUP	0.00234	0.00636
1/2*OUT^2	0.25995 *	0.06919	AO*CAP	-0.01536 *	0.00251
TER*SEC	0.04461	0.04882	CL*SUP	-0.03183 *	0.00631
TER*PRIM	0.01847	0.02418	CL*CAP	0.00493 **	0.00250
TER*OUT	-0.08337 **	0.03901	CAP*SUP	0.00182	0.00733
SEC*PRIM	-0.10722 ***	0.06331	MS*TER	-0.00399 **	0.00157
SEC*OUT	-0.01782	0.05411	MS*SEC	-0.00016	0.00287
PRIM*OUT	0.02914	0.04619	MS*PRIM	-0.00524 *	0.00183
Management Wage (MS)	0.05703 *	0.00147	MS*OUT	0.00284	0.00241
Technical and Specialist Wage (TS)	0.11290 *	0.00195	TS*TER	-0.00618 *	0.00209
Registered Nurse Wage (RN)	0.16949 *	0.00281	TS*SEC	0.01390 *	0.00382
Licenced Vocational Nurse Wage (LVN)	0.01314 *	0.00084	TS*PRIM	-0.00060	0.00242
Aides and Orderlies Wage (AO)	0.03293 *	0.00146	TS*OUT	0.00334	0.00320
Clerical Wage (CL)	0.06879 *	0.00148	RN*TER	0.00689 **	0.00299
Supplies/Equpment Price (SUP)	0.44676 *	0.00528	RN*SEC	0.00765	0.00552
Capital Price (CAP)	0.09896 *	0.00237	RN*PRIM	0.00559	0.00351
1/2*MS^2	-0.00783	0.00939	RN*OUT	-0.01463 *	0.00461
1/2*TS^2	0.00348	0.01446	LVN*TER	-0.00465 ***	0.00091
1/2*RN^2	0.10595 *	0.02209	LVN*SEC	0.00496 *	0.00164
1/2*LVN^2	0.00517	0.00801	LVN*PRIM	0.00225 **	0.00104
1/2*AO^2	0.01395	0.01123	LVN*OUT	-0.00586 *	0.00139
1/2*CL^2	0.03692 *	0.01239	AO*TER	-0.00046	0.00155
1/2*SUP^2	0.09316 *	0.01999	AO*SEC	-0.00005	0.00285
1/2*CAP^2	0.03305 *	0.00435	AO*PRIM	-0.00039	0.00181
MS*TS	0.01114	0.00885	AO*OUT	-0.00657 *	0.00241
MS*RN	0.00087	0.01027	CL*TER	-0.00655 *	0.00159
MS*LVN	0.00004	0.00536	CL*SEC	-0.00395	0.00287
MS*AO	-0.01819 **	0.00730	CL*PRIM	0.00363 **	0.00182
MS*CL	0.01822 **	0.00765	CL*OUT	0.01031 *	0.00244
MS*SUP	-0.00061	0.00631	CAP*TER	-0.00296	0.00250
MS*CAP	-0.00365	0.00252	CAP*SEC	-0.00270	0.00467
TS*RN	-0.01191	0.01234	CAP*PRIM	0.00540 ***	0.00298
TS*LVN	0.01336 **	0.00657	CAP*OUT	-0.02311 *	0.00393
TS*AO	0.03033 *	0.00895	SUP*TER	0.01790 *	0.00558
TS*CL	0.00004	0.00949	SUP*SEC	-0.01966 ***	0.01043
TS*SUP	-0.03876 *	0.00821	SUP*PRIM	-0.01062	0.00658
TS*CAP	-0.00767 **	0.00320	SUP*OUT	0.03367 *	0.00864
RN*LVN	-0.01177	0.00762	Teaching	0.31683 *	0.05457
RN*AO	0.00236	0.01100	For-Profit	-0.04916	0.03240
RN*CL	-0.00917	0.01057			

* Denotes Significance at the 1% level
** Denotes Significance at the 5% level
*** Denotes Significance at the 10% level

Table 5
Estimated Own-price elasticity for inputs

Input Price	Share	Price Elasticity	Std. Error
Management	0.064	-1.058	0.146
Technical & Specialist	0.112	-0.857	0.129
RNs	0.158	-0.171	0.140
LVNs	0.019	-0.707	0.424
Aides and Orderlies	0.037	-0.589	0.301
Clerical	0.073	-0.423	0.169
Supplies and Equipment	0.428	-0.354	0.047
Capital	0.108	-0.587	0.040

Calculated as $(\gamma_{ii}+S_iS_j)/S_i$. See Berndt (1991).

Table 6
Average Quantity Weights and Marginal Cost For Output Categories

Output Type	Avg. Quantity Weight	MC Per Discharge/Visit	Std. Error	95% CI	
Primary Discharge	1.61	4,304	1,178	1,995	6,613
Secondary Discharge	1.76	8,098	2,131	3,922	12,275
Tertiary Discharge	1.78	24,070	4,249	15,741	32,399
Outpatient Visit	0.11	207	41	126	287

Std. Errors Calculated using the Delta Method

Table 7
Function Fit

Bed Size	N	Mean Cost	Mean Predicted Costs
10-57 beds	54	24,102	26,561
58-100 beds	53	46,558	48,645
101-143 beds	53	70,469	71,531
145-215 beds	54	116,159	113,101
216-301 beds	53	177,366	170,937
305-875 beds	53	351,049	327,444

All amounts in thousands of dollars

Table 8
Scale Economies at Various Output Quantities
(Discharge & Visit Equivalents in Parenthesis)

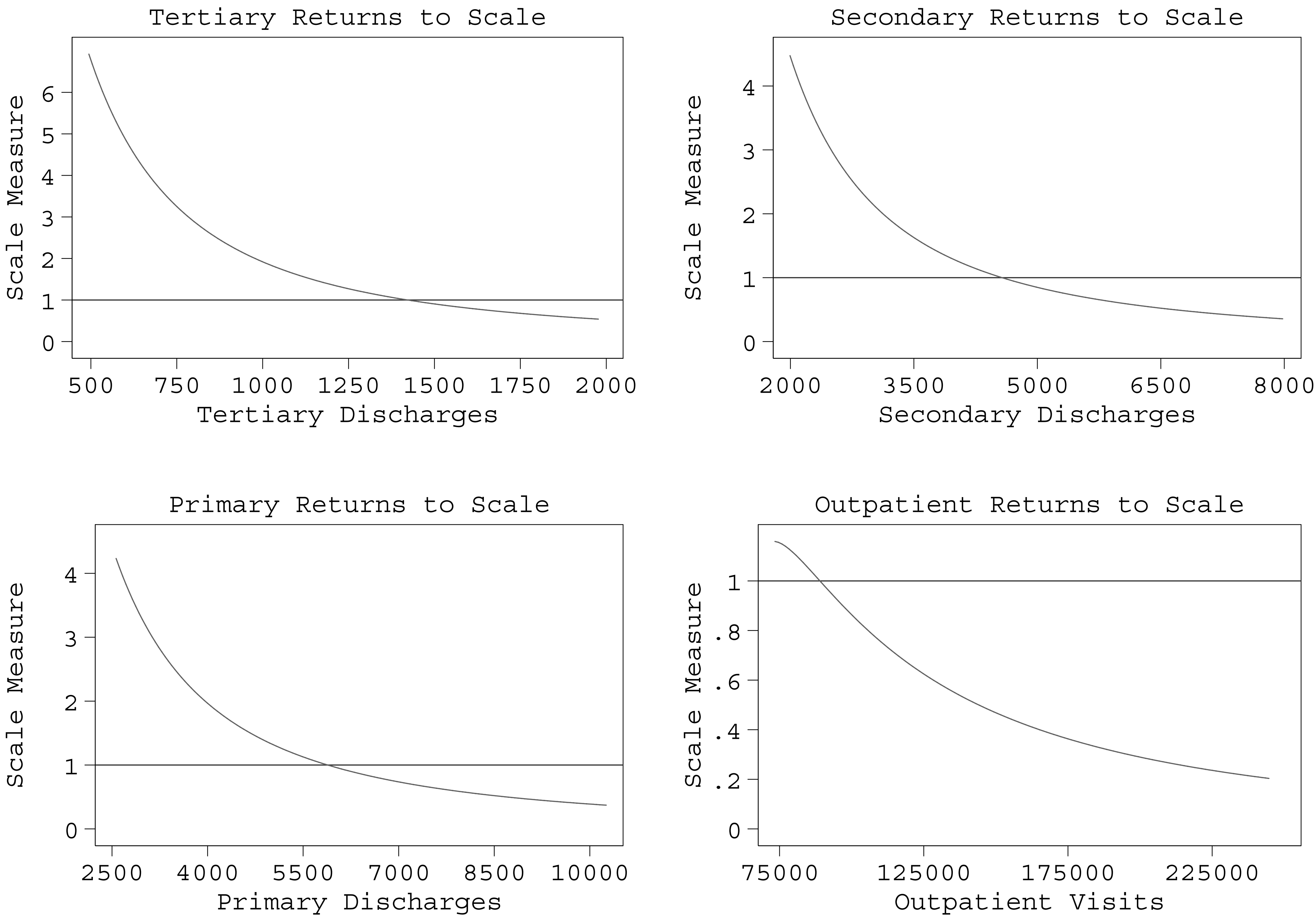
Primary	Secondary	Tertiary	Outpatient	Scale	95% CI	
8,246 (5,129)	7,035 (3,990)	1,761 (989)	12,897 (122,348)	1.161	1.076	1.246
10,307 (6,411)	8,794 (4,988)	2,201 (1,236)	16,121 (152,935)	1.019	0.931	1.107
12,369 (7,694)	10,553 (5,986)	2,641 (1,483)	19,345 (183,522)	0.927	0.824	1.029

Std. Errors Calculated Using the Delta Method

Table 9
Product Specific Scale Economies at Mean

Output Measure	Scale
Primary Care	1.27
Secondary Care	1.28
Tertiary Care	1.96
Outpatient Care	0.65

Figure 1



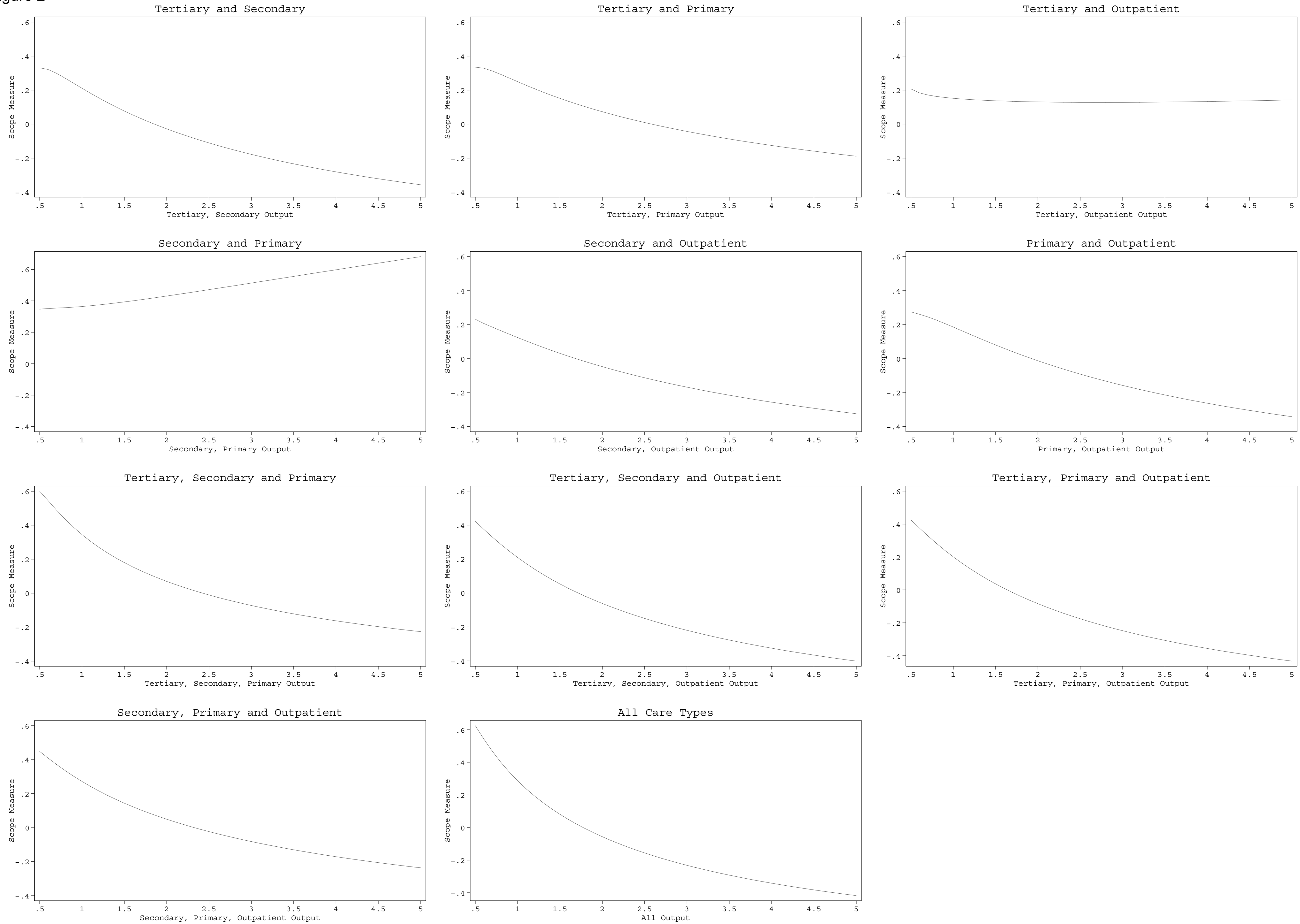
Tertiary Returns to Scale
Scale Measure
0
1
2
3
4
5
6
500
750
1000
1250
1500
1750
2000
Tertiary Discharges
Secondary Returns to Scale
Scale Measure
0
1
2
3
4
2000
3500
5000
6500
8000
Secondary Discharges
Primary Returns to Scale
Scale Measure
0
1
2
3
4
2500
4000
5500
7000
8500
10000
Primary Discharges
Outpatient Returns to Scale
Scale Measure
0
.2
.4
.6
.8
1
75000
125000
175000
225000
Outpatient Visits

Table 10
Economies of Scope at Mean Output

Output Measures	Scope (Equivalent to % savings/100)
Tertiary, Secondary	0.21
Tertiary, Primary	0.25
Tertiary, Outpatient	0.15
Seondary, Primary	0.36
Secondary, Outpatient	0.12
Primary, Outpatient	0.19
Tertiary, Primary, Secondary	0.35
Tertiary, Secondary, Outpatient	0.21
Tertiary, Primary, Outpatient	0.20
Secondary, Primary, Outpatient	0.27
Tertiary, Secondary, Primary, Outpatient	0.29

Note: μ vector=(2061,1759,440,3224) with elements corresponding to (primary,secondary,tertiary,outpatient)

Figure 2



Tertiary and Secondary
Tertiary and Primary
Tertiary and Outpatient
Secondary and Primary
Secondary and Outpatient
Primary and Outpatient
Tertiary, Secondary and Primary
Tertiary, Secondary and Outpatient
Tertiary, Primary and Outpatient
Secondary, Primary and Outpatient
All Care Types
Scope Measure
Tertiary, Secondary Output
Tertiary, Primary Output
Tertiary, Outpatient Output
Secondary, Primary Output
Secondary, Outpatient Output
Primary, Outpatient Output
Tertiary, Secondary, Primary Output
Tertiary, Secondary, Outpatient Output
Tertiary, Primary, Outpatient Output
Secondary, Primary, Outpatient Output
All Output

Figure 3

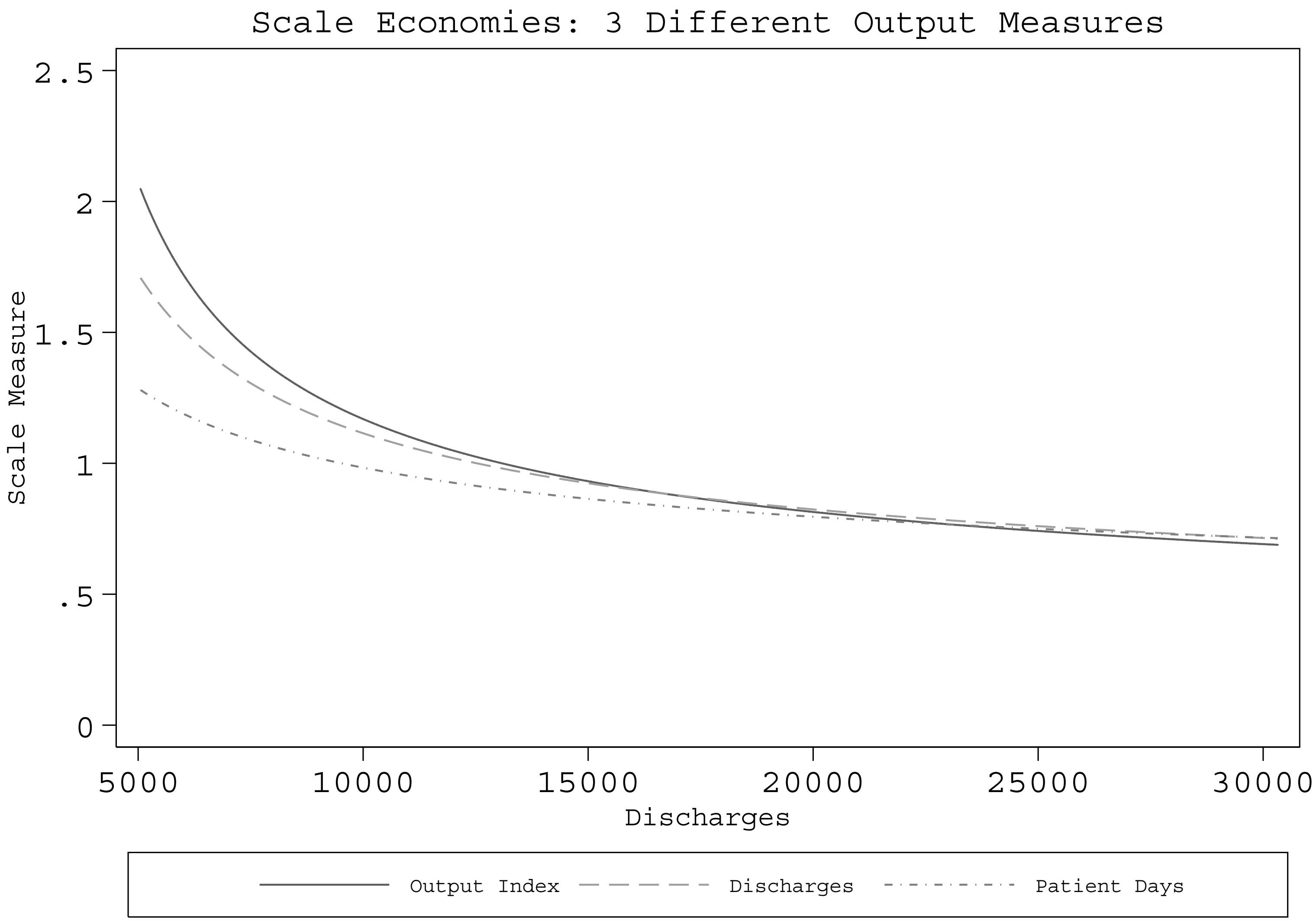

Scale Economies: 3 Different Output Measures
Scale Measure
2.5
2
1.5
1
.5
0
5000
10000
15000
20000
25000
30000
Discharges
Output Index
Discharges
Patient Days

Table 11
Scale Differences at Mean Output Using 3 Output Measures
(Bootstrapped Standard Errors in Parenthesis)

Output Measure	Classification Scheme	S_1	Output Measure	Classification Scheme	S_2	S_1-S_2
Output Index	inpat/outpat	1.05	Patient Days	inpat/outpat	0.98	0.08 (0.04)***
Output Index	inpat/outpat	1.05	Patient Days	prim/sec/ter/out	1.09	-0.03 (0.05)
Output Index	prim/sec/ter/out	1.11	Patient Days	inpat/outpat	0.98	0.14 (0.06)**
Output Index	prim/sec/ter/out	1.11	Patient Days	prim/sec/ter/out	1.09	0.02 (0.06)
Output Index	inpat/outpat	1.05	Discharges	inpat/outpat	1.11	-0.05 (0.04)
Output Index	inpat/outpat	1.05	Discharges	prim/sec/ter/out	1.13	-0.07 (0.04)
Output Index	prim/sec/ter/out	1.11	Discharges	inpat/outpat	1.11	0.01 (0.05)
Output Index	prim/sec/ter/out	1.11	Discharges	prim/sec/ter/out	1.13	-0.02 (0.05)

*** denotes significant at the 10% level
** denotes significant at the 5% level

Table 12
Efficiencies Example

Hospital	Beds	City	Ownership	Output Vector (in discharges/visits)				Predicted Cost	Predicted Merged Cost
				Primary	Secondary	Tertiary	Outpatient		
Palm Drive Hospital	49	Sebastopol	Public	607	620	64	27,057	29,236	57,774
Mendocino Coast District Hospital	52	Fort Bragg	Public	988	999	83	67,554	36,362	
St. Luke's Hospital	209	Los Angeles	Non-Profit	4,069	3,063	285	143,247	87,381	197,889
St. Francis Memorial Hopital	170	Los Angeles	Non-Profit	2,897	3,450	893	97,863	124,554	
Coalinga Regional Medical Center	78	Coalinga	Public	407	221	11	16,988	11,836	19,642
Corcoran District Hospital	32	Corcoran	Public	341	218	18	21,974	12,695	

Cost in thousands of dollars

Input prices for merged entity calculated as mean of merging entities

Table 13
Efficiencies Example

Hospital	Pre-Merger Price Per Discharge				Post-Merger Price Per Discharge				Potential For Price Increase/Decrease			
	Primary	Secondary	Tertiary	Outpatient	Primary	Secondary	Tertiary	Outpatient	Primary	Secondary	Tertiary	Outpatient
Palm Drive Hospital	9,580	9,465	39,805	190	7,728	7,946	39,718	238	19.33%	16.05%	0.22%	-25.50%
Mendocino Coast District Hospital	12,156	12,861	49,527	281								
St. Luke's Hospital	4,932	7,640	57,115	186	4,428	7,586	32,077	254	10.23%	0.71%	10.91%	-36.88%
St. Francis Memorial Hopital	8,336	13,299	36,003	222								
Coalinga Regional Medical Center	10,925	5,348	29,494	169	8,667	4,881	24,369	185	20.67%	8.73%	17.38%	-9.49%
Corcoran District Hospital	13,275	10,397	44,715	89								

Table 14

10 Most Profitable DRGs

DRG	DRG Name	Caretype	Marginal Cost	95% CI		Median Reimbursment Amt	Profit Margin
462	REHABILITATION	secondary	8,304	4,070	12,537	17,540	111%
204	DISORDERS OF PANCREAS EXCEPT MALIGNANCY	secondary	6,360	3,118	9,602	6,755	6.2%
82	RESPIRATORY NEOPLASMS	secondary	7,880	3,863	11,898	7,944	0.8%
418	POSTOPERATIVE & POST-TRAUMATIC INFECTIONS	secondary	6,106	2,993	9,219	6,120	0.2%
24	SEIZURE & HEADACHE AGE >17 W CC	secondary	5,562	2,726	8,398	5,512	-0.9%
203	MALIGNANCY OF HEPATOBILIARY SYSTEM OR PANCREAS	secondary	7,914	3,880	11,949	7,819	-1.2%
468	EXTENSIVE O.R. PROCEDURE UNRELATED TO PRINCIPAL DIAGNOSIS	secondary	24,245	11,885	36,606	23,953	-1.2%
403	LYMPHOMA & NON-ACUTE LEUKEMIA W CC	secondary	10,606	5,199	16,013	10,427	-1.7%
205	DISORDERS OF LIVER EXCEPT MALIG,CIRR,ALC HEPA W CC	secondary	7,105	3,483	10,727	6,940	-2.3%
172	DIGESTIVE MALIGNANCY W CC	secondary	8,053	3,948	12,159	7,847	-2.6%

10 Least Profitable DRGs

DRG	DRG Name	Caretype	Marginal Cost	95% CI		Median Reimbursment Amt	Profit Margin
65	DYSEQUILIBRIUM	primary	4,129	1,939	6,319	2,642	-36%
143	CHEST PAIN	primary	3,995	1,877	6,114	2,540	-36%
523	ALC/DRUG ABUSE OR DEPEND W/O REHABILITATION THERAPY W/O CC	primary	2,924	1,373	4,475	1,849	-37%
87	PULMONARY EDEMA & RESPIRATORY FAILURE	primary	12,345	5,798	18,891	7,757	-37%
321	KIDNEY & URINARY TRACT INFECTIONS AGE >17 W/O CC	primary	4,340	2,038	6,641	2,718	-37%
236	FRACTURES OF HIP & PELVIS	primary	5,884	2,764	9,004	3,637	-38%
90	SIMPLE PNEUMONIA & PLEURISY AGE >17 W/O CC	primary	4,886	2,295	7,477	3,012	-38%
139	CARDIAC ARRHYTHMIA & CONDUCTION DISORDERS W/O CC	primary	3,939	1,850	6,027	2,398	-39%
175	G.I. HEMORRHAGE W/O CC	primary	4,350	2,043	6,656	2,626	-40%
140	ANGINA PECTORIS	primary	4,352	2,044	6,659	2,598	-40%