

Do Differences in Tax Status Impact Financial Statement Comparability? Empirical Evidence from the Hospital Industry

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Abstract

Financial statement comparability is a characteristic of financial statements that allows analysts to make reliable comparisons of financial information across firms. Much of the economics and health services literature on oligopolistic behaviors in the hospital industry simply assumes, without verification, that financial statement comparability exists. If hospitals with different tax statuses are not actually comparable, any significant differences found by hospital type may be spurious. In this study, financial statement comparability is characterized using Friesner and Brajcich's (2022, 2023) information entropy theory methodology. This methodology is applied to income statement and balance sheet information drawn from a sample of California general hospitals in 2022. Quantile regression is applied to the financial statement comparability measures to assess whether hospitals with different tax statuses exhibit statistically significantly different degrees of financial statement comparability. When evaluating the 75th and 85th percentiles of the sample, government-operated, not-for-profit hospitals exhibited higher financial comparability measures than other types of firms. This indicates that these hospitals are more likely to be "outliers" compared to their peers and exhibit fundamentally different and less comparable information in their financial statements.

Keywords: financial statement comparability, hospitals, not-for-profit tax status, mixed competition

Introduction and Literature Review

Hospitals operate in a unique industry. Hospitals use a wide array of inputs to produce an equally wide array of outputs, often using very different production technologies (Gaynor, Kleiner, & Vogt, 2015). Individuals seeking hospital services often receive care in the form of a bundle of outputs, which vary from one individual to the next. The use of insurance as a third party to intermediate the pricing and payment for services leads to a lack of transparency in service pricing (Dor and Farley, 1996). Each of these factors (among a host of others) provides hospitals with a degree of market power, which typically (but not exclusively) leads to an oligopolistic market structure (Bisceglia, Padilla, Piccolo & Sääskilahti, 2023). Interestingly, within these oligopolistic markets, hospitals exhibit a variety of missions and operating objectives, as well as various tax and financial reporting obligations arising from these differing objectives (Moriya, Vogt, & Gaynor, 2010; Ghiasi, Zengul, Ozaydin, Oner, & Breland, 2018).

As a consequence, hospitals are frequently classified into groups based on their operating objectives and resulting tax status. Some hospitals are “for-profit” and are owned by residual claimants. These hospitals have a primary objective of maximizing wealth for their residual claimants, and accrue corporate income tax liabilities on any profit earned. Other hospitals have operating objectives that are primarily designed to meet a need in a community (substituting the traditional residual claimant for a community at large), and they eschew a strictly profit and/or wealth-maximizing objective in favor of meeting community needs. Because these “not-for-profit” organizations do not have residual claimants, they are not profit-driven and do not incur corporate income tax liabilities.

Numerous studies exist in the economics and health services literature on oligopolistic behaviors in the hospital industry, especially when those hospitals differ in their operating objectives (also known as “mixed competition”) (Amin, Badruddoza, & Rosenman, 2018; Levaggi & Levaggi, 2023). Empirical studies typically use data drawn from financial statements to assess the relative success (based on an assumed measure of success, whether it is productive efficiency, accumulation of market power, etc.) of for-profit and not-for-profit hospitals (Chakravarty, Gaynor, Klepper & Vogt, 2006; Ginn & Lee, 2006; Shen, Eggleston, Lau, & Schmid, 2007; Kim 2010; Collum, Menachemi, Kilgore, & Weech-Maldonado, 2014; Ghiasi, Zengul, Ozaydin, Oner, & Breland, 2018; Nurettin Oner, Zengul, Ozaydin, Hearld, & Weech-Maldonado, 2019).

Implicit in these studies is an assumption that the information drawn from the accounting statements of these firms is comparable and can be aggregated in a manner that allows for comparisons across firms with different objectives. This assumption is problematic since not-for-profit organizations take a variety of forms based on the stakeholders they serve (Cinaroglu & Zengul, 2019). Some are operated as state or local government agencies, while others are affiliated with private stakeholder groups (Nurettin *et al.*, 2019). As the objectives of these organizations vary, so do resource flows and the summaries of those flows as depicted in accounting statements. The more diverse the objectives, the less tenable the assumption of comparability. Thus, any significant differences found by hospital type may be due to systematic differences in decisions made by management across these hospitals, differences in financial statement comparability across these hospitals (i.e., a violation of a key assumption underlying those studies), or a combination of the two. One notable exception to this trend is Brajcich, Friesner, and McPherson (2024), who conducted a financial statement comparability analysis on a mix of for-profit, private not-for-profit, and government hospitals in Washington state. This study empirically examined whether hospitals that hold specific types of intangible assets (goodwill, etc.) were more or less financially comparable to other hospitals that do not hold these types of intangible assets. The

authors found that hospitals holding specific types of intangible assets did exhibit significant differences in financial statement comparability. However, they did not control for the profit status of these firms in the analysis.

An issue complicating the assessment of financial statements across hospitals with different tax status is that the most common empirical methodology used to assess financial statement comparability (De Franco, Kothari, & Verdi, 2011) is only applicable to firms with a profit or wealth-maximizing objective. More specifically, De Franco *et al.* (2011) assume that all relevant financial statement information is fully characterized by the earnings of the firm. Similarly, the return on a firm's stock price is used to capture all economic events relevant to the firms in the sample. This allows for the creation of a simple regression, where the return on a firm's stock price is regressed on earnings. The difference between predicted and actual earnings is used to create a measure of financial statement comparability between a given firm and its peers. As noted above, this methodology has been used extensively in the literature to empirically assess the causes and consequences of differing levels of financial statement comparability on firm decisions (Kim, Li, Lu, & Yu, 2016; Imhof, Seavey, & Smith, 2017; Chen & Gong 2018; Choi, Choi, Myers, & Ziebart, 2019; Chircop, Collins, Helge Hass, & Nguyen, 2020; Do, 2021; Jiu, Hu, & Liu, 2021). The challenge inherent in this approach is that firms holding not-for-profit tax status do not generally exhibit stock price returns or earnings. Thus, the De Franco *et al.* (2011) methodology cannot be applied to markets or industries in which mixed competition occurs.

Two alternatives exist in the literature to assess financial statement comparability within the context of mixed competition. The first was developed by Hoitash, Hoitash, Kurt, and Verdi (2023), who used perceptual information elicited from analysts and corporate boards to define a particular company's peers, and by extension to characterize financial statement comparability. This methodology can be applied to all firms, regardless of tax status. The primary limitation of this methodology is the reliance on the subjective assessments of industry experts, rather than information drawn directly from financial statements. Another alternative applies information entropy theory to data drawn directly from firm financial statements to create an aggregate financial statement comparability measure (Friesner & Brajcich, 2022a; Friesner & Brajcich, 2023). Moreover, this methodology was specifically developed to assess financial statement comparability in markets or industries where mixed competition may exist. At least one study has shown that this methodology produces reliable and consistent results when applied to hospital markets (Friesner & Brajcich, 2022b). The primary drawback of this methodology is that, as a relatively new methodology, only a few studies have used it to assess financial statement comparability in markets experiencing mixed competition (Friesner, 2025; Friesner, Brajcich, Friesner, and McPherson, 2025).

This study empirically assesses whether the financial accounting statements of hospitals with different tax status, classified as for-profit or various categories of not-for-profit organizations, are systematically comparable. Researchers and policymakers have access to financial statement information more frequently than they have access to (valid and reliable) subjective perceptions of industry analysts. As a result, the information entropy-based methodology is used to empirically characterize financial statement comparability. In doing so, this study also contributes to the small, but growing, literature that uses information entropy-based methods to evaluate financial statement comparability across firms.

The remainder of this manuscript proceeds as follows. The next section develops the primary null hypothesis utilized in the study, summarizes the empirical methodology that is used to characterize financial statement comparability, and describes the statistical methodologies used

to evaluate the study's null hypothesis. The third section describes the data used in the study, which consists of income statement and balance sheet information drawn from a sample of general, acute care hospitals operating in California during the 2022 calendar year. The fourth section presents the empirical results. The paper concludes by discussing the implications of the results for managerial decision-making and public policy, identifying the major limitations of the study, and presenting some opportunities for future research.

Empirical Methodology

The literature review generates two primary implications that guide the current analysis. First, while there is a robust literature on financial statement comparability, it is limited to publicly traded firms with a wealth-maximizing objective. Second, there is a new methodology that can be used to assess financial statement comparability across firms with different operating objectives and tax statuses, but that methodology has only infrequently been applied to hospitals operating in a mixed competitive environment. Given the paucity of information regarding the causes and consequences of financial statement comparability among hospitals in mixed competitive markets, this study adopts an exploratory framework with parsimony as the guiding principle. That is, the study seeks to impose as little prior structure as possible on the relationship between financial statement comparability and the operating objectives of these hospitals. When empirically evaluating the relationship between financial statement comparability and operating objectives, it chooses the empirical techniques that are appropriate, but as simple (or as simply specified) as possible. Therefore, this operates under the following general null and alternative hypotheses:

H_0 : No relationship between the tax status and/or operating objectives of the hospital and financial statement comparability.

H_A : Not H_0 .

The Friesner and Brajcich (2022, 2023) methodology (denoted as FB) assumes the existence of one or more valid, reliable, and consistently reported accounting statements. Adherence to Financial Accounting Standards Board (FASB) generally accepted accounting principles, or another analogous set of standards, is sufficient to ensure the existence of valid, reliable and consistently reported financial statements. We are careful to note that adherence to FASB standards is a necessary, but not sufficient, condition to ensure financial statement comparability. To achieve financial statement comparability, firms must not only use consistently defined standards to collect and report information, but also make consistent operational decisions that lead to similar flows of funds, which are ultimately captured by financial statements.

Each accounting statement reports a series of J categories that are mutually exclusive and collectively exhaustive. This allows each of these J categories to be reported in common form. For example, in an income statement, firm expenses are typically reported as a series of $j = 1, \dots, J$ expense categories (salaries and wages, supplies, etc.) which sum to total expenses. In common form, the proportion of total form expenses in each of these expense categories would be reported and utilized in the financial statement comparability analysis. Define $q_j, j = 1, \dots, J$ as the set of these J proportions. As an aside, this methodology can be generalized to incorporate information from multiple accounting statements, or sets of information within an accounting statement, so long as the included information can be reported in common form.

Establishing financial statement comparability requires the creation of (relative) benchmarks, against which each empirical proportion (q_j) can be evaluated. Define these

benchmark proportions as p_j , $j = 1, \dots, J$. The larger the difference (whether positive or negative) between each q_j and corresponding p_j , the less optimal is the q_j . The common form property of the financial statement creates an inter-relationship between financial statement comparability in one category and overall financial statement comparability across all J categories. That is, if one firm's q_j dramatically exceeds its corresponding p_j benchmark, at least one of the firm's other q_j s must be below its corresponding p_j . Additionally, the use of a common (optimal) benchmark across all firms in a market or an industry allows for the determination of financial statement comparability. If the set of q_j s for a given firm deviates markedly from the p_j values, but another firm's q_j values are (when considered collectively) very close to the same p_j values, the two firms are less likely to be financially comparable.

A critical factor in assessing financial statement comparability is the identification of the optimal benchmarks. The FB methodology uses the concept of minimum cross entropy (Golan, Judge, & Miller, 1996; Golan, 2006) to calculate these benchmarks. Mathematically, for one firm (firm i) and one set of mutually exclusive and collectively exhaustive accounting statement information, cross-entropy is an optimization problem of the following form:

$$\min_{p_1, \dots, p_J} CE_i = \sum_{j=1}^J p_j \log_2 \left(\frac{p_j}{q_{ij}} \right) \quad (1)$$

Subject to the following constraints, which ensure proper probabilities:

$$\sum_{j=1}^J p_j = 1; p_j \geq 0 \forall j = 1, \dots, J;$$

$$\sum_{j=1}^J q_{ij} = 1; q_{ij} \geq 0 \forall j = 1, \dots, J; \text{ and } \forall i = 1, \dots, n;$$

$$p_j \log_2 \left(\frac{p_j}{q_{ij}} \right) = 0 \text{ when either } p_j = 0 \text{ or } q_{ij} = 0$$

where:

CE_i is the overall cross-entropy score for firm i and all other variables are as previously defined.

The goal of the programming problem identified in (1) is to strike a balance between assuming as little as possible about the optimal benchmarks, while simultaneously attempting to ensure that the benchmarks match the trends observed in the empirically observed proportions. Because each of the benchmark proportions is shared across firms in the sample, financial statement comparability can be assessed in two ways. The first, as noted above, is to compare a single q_j to its corresponding p_j , and to repeat this process (for the same category, j) for another firm in the sample, and subsequently compare trends across firms. This is relatively tedious, especially when the number of financial statement categories (J) is large.

An alternative, and more efficient means to assess financial statement comparability is to examine the overall CE_i metric for each firm. FB suggest normalizing each CE_i using the z-score transformation. While the absolute (cardinal) magnitude of the CE_i does not have a direct interpretation, the z-score transformed CE_i variable does give information on where a given firm's CE_i is positioned relative to other firms in the sample. Firms with z-score transformed CE_i values between -1 and +1 are considered to be relatively close peers to each other. Concomitantly, firms with z-score-transformed CE_i values beyond -2 or +2 are considered outliers who are not close peers to most other firms in the data set. Because these firms are not close peers, they are less financially comparable to other firms in the data set. Similarly, a firm that carries a z-score-transformed CE_i of +1.5 would be considered as less of a peer (and less financially comparable) to another firm whose CE_i value is -0.9, especially if many other firms in the sample carried z-score-transformed CE_i values between -0.9 and +1.5. Implicit in this transformation and interpretation of the CE_i variable is that the researcher is most interested in the (ordinal) relative

positioning (and rank ordering) of CE_i across firms in the data set. The cardinal magnitude of the z-score-transformed CE_i variable (hereafter denoted as $z\text{-score}(CE_i)$) only matters in identifying the firm as an outlier.

A primary benefit of the cross-entropy formulation is that it exhibits the mathematical property of additivity. That is, equation (1) can be extended to include any number of sets of financial statement information. If the set of q_j s evaluated in equation (1) are mutually exclusive and collectively exhaustive expense categories drawn from the income statement, another term can be added to equation (1) covering $k = 1, \dots, K$ mutually exclusive and collectively exhaustive revenue categories drawn from the same income statement. In theory, the cross-entropy formulation can account for any number of sets of financial statement information, so long as the financial statement information can be expressed in common form. When summed over all sets of financial information, and when minimized over all $i=1, \dots, n$ firms in the dataset, a very simple, general representation of cross-entropy as a constrained quadratic programming problem is achieved.

$$\min_{p_1, \dots, p_J, \dots, \rho_1, \dots, \rho_K} \sum_{i=1}^n CE_i = \sum_{i=1}^n \left(= \sum_{j=1}^J p_j \log_2 \left(\frac{p_j}{q_{ij}} \right) + \dots + \sum_{k=1}^K \rho_k \log_2 \left(\frac{\rho_k}{r_{ik}} \right) \right) \quad (2)$$

Subject to the general constraint that all relevant proportions are proper and the entropy formula is not undefined:

$$\begin{aligned} \sum_{j=1}^J p_j &= 1; p_j \geq 0 \forall j = 1, \dots, J; \\ \sum_{k=1}^K \rho_k &= 1; \rho_k \geq 0 \forall k = 1, \dots, K; \\ \sum_{j=1}^J q_{ij} &= 1; q_{ij} \geq 0 \forall j = 1, \dots, J; \text{ and } \forall i = 1, \dots, n; \\ \sum_{k=1}^K r_{ik} &= 1; r_{ik} \geq 0 \forall k = 1, \dots, K; \text{ and } \forall i = 1, \dots, n; \\ p_j \log_2 \left(\frac{p_j}{q_{ij}} \right) &= 0 \text{ when either } p_j = 0 \text{ or } q_{ij} = 0 \\ \rho_k \log_2 \left(\frac{\rho_k}{r_{ik}} \right) &= 0 \text{ when either } \rho_k = 0 \text{ or } r_{ik} = 0 \end{aligned}$$

The general specification outlined in equation (2) facilitates hypothesis testing in both univariate and multivariate statistical analyses. The study's general null hypothesis of no significant relationship between the tax status of the hospital and financial statement comparability can be formally re-stated as:

H_0 : No mean/median differences exist in CE_i across groups of firms as defined by tax status.
 H_A : Not H_0 .

Operationalizing the null hypothesis within the context of this study becomes a straightforward process. Under the null hypothesis, the rank ordering of CE (or $z\text{-score}(CE_i)$) across firms should not vary systematically based on the tax status. Within the context of univariate hypothesis testing, this implies that the null hypothesis can be evaluated using Kruskal-Wallis (nonparametric, one-way ANOVA) and median sign tests.

Using multivariate regression techniques to evaluate the null hypothesis, while controlling for the regulatory, socio-economic, and epidemiologic characteristics facing each firm in the sample, is a more complicated endeavor. This analysis follows FB's suggestion to utilize quantile regression, with $z\text{-score}(CE_i)$ serving as the dependent variable in the regression (Koenker &

Hallock, 2001; Huang, Zhang, Chen, & He, 2017). Because the study is exploratory and emphasizes parsimony, a linear-in-parameters, reduced-form response function is postulated:

$$\min_{\alpha, \beta_1, \dots, \beta_L, \gamma_1, \dots, \gamma_\Psi} \sum_{i=1}^n \theta_\pi(\cdot) (z\text{-score}(CE_i) - \alpha - \sum_{l=1}^L \beta_l X_{li} - \sum_{\psi=1}^\Psi \gamma_\psi Z_{\psi i}) \quad (3)$$

where:

$R = \alpha + \sum_{l=1}^L \beta_l X_{li} + \sum_{\psi=1}^\Psi \gamma_\psi Z_{\psi i}$ is the linear-in-parameters, reduced-form response function;

the β s, γ s, and α are parameters to be estimated;

X_{li} represents a series of $l = 1, \dots, L$ exogenous variables characterizing a firm's legal status, tax status, or another measure of a firm's operating objectives;

$Z_{\psi i}$ represents a series of $\psi = 1, \dots, \Psi$ exogenous control variables characterizing a firm's regulatory, socio-economic, or epidemiological characteristics;

$i = 1, \dots, n$ denotes each firm in the sample;

$\theta_\pi(\cdot)$ denotes the absolute value function that yields the π^{th} percentile as its optimal solution (Koenker and Hallock, 2001); and

all other notation is as defined previously.

As long as the response function is specified as linear in parameters, equation (3) can be solved for any given specification of π using linear programming (Koenker & Hallock, 2001). Hypothesis testing on individual parameter estimates can be conducted using t-tests. The degrees of freedom for a given t-test is equal to the sample size less the total number of slope coefficients.

Under the null hypothesis, the coefficient estimate for any tax status should be zero, holding the effects of the other specified regressors constant. T-tests on individual parameter estimates are used to assess the statistical significance of the coefficient estimate for any tax status.

Quantile regression can be framed to predict any percentile of interest in the dependent variable. Most standard applications of quantile regression focus on predicting the median of the dependent variable. The financial statement comparability metric CE_i (and $z\text{-score}(CE_i)$) may be interpreted in both a rank-ordered and an outlier-detection framework. Several versions of equation (3) are estimated, each time specifying a different percentile of interest for the dependent variable. Percentiles closer to 0 or 100 are interpreted as regressions predicting the likelihood that a firm is a positive or negative outlier in the data set. Consistent with the literature, the primary percentile of interest in this study is the median for $z\text{-score}(CE_i)$. Additionally, equation (3) is estimated by predicting the 15th, 25th, 75th, and 85th percentiles of $z\text{-score}(CE_i)$.

When estimating each quantile regression, several standard econometric adjustments are made to ensure that the model produces viable results. For example, if there a $h = 1, \dots, H$ mutually exclusive and collectively exhaustive regressors (typically binary variables or proportional variables identifying groups of firm-specific characteristics), only $H-1$ of these variables are included in the regression to reduce the possibility of perfect multicollinearity. All coefficient estimates are interpreted relative to the omitted variable. Similarly, to reduce the likelihood of heteroskedasticity, quantitative variables with very large measures of dispersion are transformed using the natural logarithm. All statistical analyses were assessed using the IBM Statistics Version 29 analysis package. All hypothesis tests were evaluated using a 5 percent significance level.

Data

The data used in this manuscript were drawn from acute care hospitals operating in the state of California during the 2022 calendar year. This represents the most recent year of available data at the time this study was conducted. Each year, the California Office of Health Care Access and Information (HCAI) requires each hospital in the state to submit a full set of financial statements (including an income statement and balance sheet), as well as select patient care volume, service indicator information, and patient demographic information. The Department of HCAI audits, cleans, and subsequently makes the data publicly available at (<https://hcai.ca.gov/data/datasets/>). Because the data are aggregated to, and reported at, the level of the hospital (rather than an individual), and are entirely in the public domain, the analysis of the data is not considered human subjects research and is not subject to Institutional Review Board approval by the authors' institutions.

The financial comparability metric is created using information drawn from both the income statement and the balance sheet of these hospitals. With regard to balance sheet information, four mutually exclusive and collectively exhaustive categories of assets were created, as well as three mutually exclusive and collectively exhaustive categories of liabilities. These categories are consistent with common use and interpretation of balance sheet information and fulfill FB's requirement that variables be expressed in common form. The asset categories are accounts receivable, current assets, net property, plant, and equipment, and all other non-current assets. Liability categories include current liabilities, deferred credits, and non-current liabilities (which is primarily comprised of long-term debt).

Revenue and expense information, drawn from the income statement, were also used in the creation of the financial comparability metric. Analogous to the balance sheet information described above, revenue information was aggregated into three mutually exclusive and collectively exhaustive categories. These can be expressed in common form: patient services revenue (net of all discounts and contractual adjustments), other operating revenue, and non-operating revenue. Expenses are characterized by the type of input used and the practice in which the expense was accrued. Both sets of expense categories are mutually exclusive and collectively exhaustive. Thus, each set of expense categories, by itself, comprehensively accounts for total hospital expenses. There are two reasons why both formulations were included in the creation of the financial comparability metric. First, each set of expenses expresses fundamentally unique information about the utilization of resources within a hospital. Second, the FB methodology allows for the inclusion of both sets of expense information.

Expenses by input category were allocated into one of six mutually exclusive and collectively exhaustive categories: salaries and benefits, professional fee expenses, supply expenses, purchased service expenses, capital (rent, depreciation, lease and interest) expenses, and all other input expenses. Expenses by area of use were allocated into one of eight mutually exclusive and collectively exhaustive categories: inpatient care, ambulatory care, ancillary services, research and educational activities, general services, fiscal management services, general administrative services, and all other activity expenses.

A number of variables were created to characterize the tax status of each hospital, other measures that (directly or indirectly) characterize the objectives of a hospital, and the socio-economic and epidemiologic environment in which these hospitals operate. A series of binary variables were created to reflect the tax status of each firm. All hospitals were categorized as either for-profit, private not-for-profit, or government-operated not-for-profit. In addition, information was collected on hospital operating characteristics, including hospital full-time equivalent

employee counts (FTEs), the distribution of hospital FTEs by scope of practice (medical staff, nursing staff, etc.), the number of licensed beds (both overall and distributed by area of care), and hospital outputs (inpatient days and outpatient visits, disaggregated by third-party payer). Lastly, several variables were created to characterize the external and regulatory environment in which a hospital operates. More specifically, binary variables were created to indicate whether a given hospital is located in a rural area, and whether a hospital is classified as a teaching hospital. Additionally, California is disaggregated into 14 mutually exclusive and collectively exhaustive health services areas (HSAs), which are meant to account for both geographic considerations and unique communities that primarily reside in those areas. We included a series of binary variables identifying the HSA in which a hospital operates.

Results

During the 2022 calendar year, there were a total of 444 hospitals in California. Of these 444 hospitals, 162 were eliminated from the sample because they did not operate for a full year or provided unreliable information. Examples of the latter include a failure to report a complete balance sheet and income statement, misreported information (categories of expenses do not sum to total expenses, etc.), and a failure to provide a complete set of demographic information. The vast majority of eliminated hospitals failed to report a full set of financial information to the Department of HCAI. This left a working sample of 282 observations.

Table 1 contains the names, definitions, and descriptive statistics for each of the variables in the data set. At the sample mean, the typical hospital generated \$331,325,565.66 in revenues during the 2022 calendar year. Of these revenues, approximately 93.1 percent was derived from direct patient care activities. Concomitantly, at the mean, the typical hospital generated \$324,846,629.28 in expenses in 2022. When disaggregated by activity, approximately 24.1 percent was generated through the provision of inpatient care, 22.0 percent through ancillary services, 17.8 percent through administrative services, and the remainder through other productive activities. When disaggregated by input usage, 48.1 percent of expenses were attributed to salaries and wages, 14.8 percent to purchased services, 10.6 percent to supplies, 10.4 percent to professional fees, and the remainder to other inputs.

At the sample mean, the typical hospital had \$462,926,576.62 in assets in 2022, of which 31.1 percent was held in other current assets, 29.9 percent in net property, plant, and equipment, 20.9 percent in other non-current assets, and 19.0 percent in accounts receivable. The sample mean for hospital liabilities was \$308,676,750.70 in 2022. Of these liabilities, 64.2 percent were held as current liabilities, 30.7 percent were in non-current liabilities, and 5.0 percent in deferred credits. The standard deviations for all revenue, expense, asset, and liability variables are larger in magnitude than their corresponding mean values, which suggests substantial variability in the revenue and expense, as well as asset and liability, positions across hospitals in the sample.

Table 1. Descriptive Statistics [n=282]

<u>Variable</u>	<u>Description</u>	<u>Mean</u>	<u>Std. Deviation</u>
<i>Hospital Revenue Information</i>			
trevenues	Total hospital revenues	\$331,325,565.66	\$548,217,042.23
pnetptev	Proportion of total revenue generated by net patient services revenue	0.931	0.098
pothoprev	Proportion of total revenue generated by other operating revenue	0.030	0.049
pnonoprev	Proportion of total revenue generated by non-operating revenue	0.038	0.084
<i>Hospital Expense Information - Reported by Service Activity</i>			
texpenses	Total hospital expenses	\$324,846,629.28	\$536,711,761.77
pexp hosp	Proportion of expenses generated by providing inpatient care services	0.241	0.122
pexp amb	Proportion of expenses generated by providing ambulatory care services	0.091	0.077
pexp anc	Proportion of expenses generated by providing ancillary services	0.220	0.115
pexp purchased	Proportion of expenses generated through purchased (inpatient & outpatient) services	0.009	0.031
pexp research	Proportion of expenses generated by research and educational activities	0.005	0.013
pexp general	Proportion of expenses generated through the provision of general services	0.143	0.038
pexp fiscal	Proportion of expenses generated through fiscal management activities	0.036	0.022
pexp admin	Proportion of expenses generated through administrative activities	0.178	0.069
pexp other	Proportion of expenses generated through other activities	0.076	0.072
<i>Hospital Expense Information - Reported by Input Category</i>			
psalben	Proportion of total expenses from salary, wage and benefit expenses	0.481	0.093
pprofessional	Proportion of total expenses from professional fee expenses	0.104	0.060
psupp	Proportion of total expenses from supply expenses	0.106	0.056
ppurchased	Proportion of total expenses from purchased service expenses	0.148	0.081
prli	Proportion of total expenses from rental, lease, depreciation, and interest expenses	0.064	0.041
pins	Proportion of total expenses from insurance-related expenses	0.007	0.005

poth	Proportion of total expenses from all other expense categories	0.090	0.077
Hospital Asset Information			
tassets	Total hospital assets	\$462,926,576.62	\$932,486,820.93
pacctrec	Proportion of assets held in accounts receivable (less unrecoverables)	0.190	0.162
pocasst	Proportion of assets held in other current assets	0.311	0.262
pnppe	Proportion of assets held in net property, plant and equipment	0.290	0.214
pothasst	Proportion of assets held in other, non-current assets	0.209	0.236
Hospital Liability Information			
tliabilities	Total hospital liabilities	\$308,676,750.70	\$884,559,868.01
pcurliab	Proportion of liabilities held in current liabilities	0.642	0.317
pdefcred	Proportion of liabilities held in deferred credits	0.050	0.130
pltdebt	Proportion of liabilities held in long term debt	0.307	0.309
Hospital Inputs, Outputs, Characteristics and Demographic Information			
hospfte	Total hospital full time equivalent employees	1032.680	1482.493
pnurfte	Proportion of hospital full time equivalent employees who are nurses	0.379	0.105
medstaff	Total medical staff	337.180	477.204
tdays	Total inpatient days	44353.260	44060.753
pdaycr	Proportion of inpatient days generated by patients insured through Medicare (traditional and managed care)	0.381	0.207
pdaycd	Proportion of inpatient days generated by patients insured through Medicaid/MediCal (traditional and managed care)	0.362	0.232
pdayth	Proportion of inpatient days generated by patients insured through private, third party insurers (traditional and managed care)	0.198	0.183
pdayoth	Proportion of inpatient days generated by patients insured through all other insurers	0.060	0.172
tvisits	Total outpatient visits	116424.420	209070.771
vistotdv	Binary variable identifying those hospitals that provided outpatient care	0.870	0.334

pviscr	Proportion of total outpatient visits generated by patient insured through Medicare (traditional and managed care)	0.267	0.187
pviscd	Proportion of total outpatient visits generated by patients insured through Medicaid/MediCal (traditional and managed care)	0.285	0.230
pvisth	Proportion of total outpatient visits generated by patients insured through private, third party insurers (traditional and managed care)	0.271	0.214
pvisoth	Proportion of total outpatient visits generated by patients insured through all other insurers	0.050	0.094
pviser	Proportion of total outpatient visits provided through the hospital's emergency department	0.326	0.314
pvisclin	Proportion of total outpatient visits provided through the hospital's outpatient clinics	0.207	0.284
pvishome	Proportion of total outpatient visits provided through the hospital's home health care services	0.009	0.041
pvisref	Proportion of total outpatient visits provided through all other outpatient care (primarily other outpatient referrals)	0.234	0.230
licbeds	Number of licensed beds	199.860	172.090
pstaff	Proportion of licensed beds that are staffed	0.643	0.200
pbdacute	Proportion of licensed beds devoted to acute care	0.655	0.392
pbedpsyc	Proportion of licensed beds devoted to psychiatric care	0.174	0.338
pbedchem	Proportion of licensed beds devoted to chemical dependency care	0.011	0.087
pbedrehab	Proportion of licensed beds devoted to rehabilitation-related care	0.042	0.166
pbedltc	Proportion of licensed beds devoted to long term care	0.115	0.235
pbedoth	Proportion of licensed beds devoted to all other types of care	0.002	0.033
fpdv	Binary variable identifying investor-owned (for-profit) hospitals	0.420	
npdv	Binary variable identifying privately-controlled, not-for-profit hospitals	0.410	

govdv	Binary variable identifying government-operated (not-for-profit) hospitals	0.170	
ruraldv	Binary variable identifying hospitals located in rural areas	0.160	
teachdv	Binary variable identifying hospitals that are designated as teaching hospitals	0.080	
HSA1	Binary variable identifying hospitals located in HSA 1 - Northern California	0.060	
HSA2	Binary variable identifying hospitals located in HSA 2 - Golden Empire	0.060	
HSA3	Binary variable identifying hospitals located in HSA 3 - North Bay	0.040	
HSA4	Binary variable identifying hospitals located in HSA 4 - West Bay	0.050	
HSA5	Binary variable identifying hospitals located in HSA 5 - East Bay	0.060	
HSA6	Binary variable identifying hospitals located in HSA 6 - North San Joaquin	0.050	
HSA7	Binary variable identifying hospitals located in HSA 7 - Santa Clara	0.030	
HSA8	Binary variable identifying hospitals located in HSA 8 - Mid-Coast	0.040	
HSA9	Binary variable identifying hospitals located in HSA 9 - Central	0.060	
HSA10	Binary variable identifying hospitals located in HSA 10 - Santa Barbara/Ventura	0.030	
HSA11	Binary variable identifying hospitals located in HSA 11 - Los Angeles	0.250	
HSA12	Binary variable identifying hospitals located in HSA 12 - Inland Counties	0.130	
HSA13	Binary variable identifying hospitals located in HSA 13 - Orange	0.070	
HSA14	Binary variable identifying hospitals located in HSA 14 - San Diego/Imperial	0.060	

When evaluated at the same mean, the average hospital employed 1032.68 FTE employees, of which 37.9 percent were employed as nurses. There were also 337.18 medical staff at the typical hospital. Hospitals provided 44,353.26 inpatient days of care, with 38.1 percent provided to Medicare patients and another 36.2 percent provided to MediCal (California's Medical program) patients. Eighty-seven percent of hospitals provided outpatient care services, and a typical hospital provided 116,424.42 outpatient visits, with 32.6 percent funneled through the emergency department and 20.7 provided through outpatient clinics. Of these 116,424.42 visits, 26.7 percent were provided to Medicare patients, 28.5 percent to MediCal patients, and 27.1 percent to privately insured patients. At the sample mean, the average hospital held 199.86 licensed beds, of which 64.3 percent were staffed. Moreover, 65.5 percent of licensed beds were allocated to the provision of acute care, 17.4 percent to psychiatric care, and 11.5 percent to long-term care.

Of the 282 firms in the sample, 42.0 percent were owned and operated as a for-profit (investor-owned) organization, 41.0 percent were operated as private, not-for-profit hospitals, and 17.0 percent were operated by a government agency. Sixteen percent of hospitals were located in rural areas, and 8.0 percent were designated as teaching hospitals. Lastly, 25.0 percent of hospitals were located in the Los Angeles HSA (HSA 11), and 13.0 percent were located in the Inland HSA (HSA 12). All other hospitals in the sample were relatively evenly distributed across the remaining 12 HSAs.

The nonlinear programming problem (equation (2)) was used to create the financial comparability variable (CE_i). Table 2 contains the results from this analysis. The optimal benchmark proportions (OBP) are roughly similar, although not identical, to the sample proportions (SP) reported in Table 1. For example, the OBP of revenues derived from patient care (net of deductions, etc.) was 97.3 percent, compared to the SP of 93.1 percent. Similarly, the OBP of expenses for salary and wage expenses was 52.1 percent (SP: 48.1 percent); for purchased services, they were 14.1 percent (SP: 14.8 percent), and for supplies they were 9.9 percent (SP: 10.6 percent). One interesting deviation between the OBPs and the SPs was found among expenses disaggregated by area of use. For example, the OBP of expenses allocated to purchased services was 39.8 percent (SP: 0.9 percent), the OBP of expenses related to inpatient care was 14.6 percent (SP: 24.1 percent), the OBP of ancillary services was 12.0 percent (SP: 22.0 percent), and the OBP of administrative expenses was 11.1 percent (SP: 17.8 percent).

With regard to asset and liability categories, the OBPs largely coincide with the SPs. The four OBPs for assets are: 23.0 percent for accounts receivable (SP: 19.0 percent), 28.7 percent for current assets (SP: 31.1 percent), 30.9 percent for net property, plant and equipment (SP: 29.0 percent), and 17.3 percent for all other non-current assets (SP: 20.9 percent). The three OBPs for liabilities are 55.9 percent for current liabilities (SP: 64.2 percent), 10.4 percent for deferred credits (SP: 5.0 percent), and 33.8 percent for long-term debt (SP: 30.7 percent).

Lastly, Table 2, Panel 2 provides descriptive statistics for the overall cross-entropy measure (CE_i). Examining the percentiles for the untransformed variable suggests that the variable's distribution is skewed and unlikely to be closely approximated by a normal distribution.

Table 2. Optimization Results [n=282]

<i>Panel A: Optimal Proportions</i>	
<u>Category</u>	<u>Optimal P_i</u>
pnetptev	0.973
pothoprev	0.012
pnonoprev	0.015
pexphosp	0.146
pexpamb	0.060
pexpanc	0.120
pexppserv	0.398
pexpresed	0.012
pexpgen	0.093
pexpfis	0.021
pexpadm	0.111
pexpoth	0.040

psalben	0.521
pproffees	0.095
psupp	0.099
ppurserv	0.141
prli	0.059
pins	0.006
poth	0.079
pacctrec	0.230
pocasst	0.287
pnppe	0.309
pothasst	0.173
pcurliab	0.559
pdefcred	0.104
pltdebt	0.338
Overall Entropy Measure	348.537

Panel B: Descriptive Statistics for the Overall Entropy Measure							
<u>Variable</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>15th %</u>	<u>25 %</u>	<u>Median</u>	<u>75 %</u>	<u>85th %</u>
CE	1.236	1.252	0.115	0.375	0.989	1.762	2.303
Z(CE)	0.000	1.000	-0.895	-0.688	-0.197	0.420	0.852

Table 3 contains the Kruskal-Wallis and median sign tests examining the statistical significance of the relationship between the overall financial comparability metric (z-score(CE_i)) and the distribution of firms by tax status (for-profit, private not-for-profit, and government-operated). The probability values for both the Kruskal-Wallis test (prob.: 0.156) and the median sign test (prob. = 0.072) both fail to reject the null hypothesis of no mean/median differences in the financial comparability variable (z-score(CE_i)) by tax status at a five percent significance level.

Table 3: Nonparametric Analysis of Entropy Values by Profit Status [n=282]

<u>Variable</u>	<u>No. Hospitals</u>	Non-Standardized		Z-Score Standardized		Kruskal-Wallis	<u>Prob.</u>	Median Sign	<u>Prob.</u>
		<u>Mean</u>	<u>Std. Dev.</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Test Statistic</u>		<u>Test Statistic</u>	
fpdv	118	1.308	1.123	0.058	0.897	3.172	0.156	5.265	0.072
npdv	117	1.139	1.186	-0.077	0.947				
govdv	47	1.295	1.669	0.047	1.333				

* indicates statistical significance at the 5% level or better

Table 4 contains the first set of quantile regression results, which predict the median value for z-score(CE_i). The coefficient estimates for both the private not-for-profit (npdv; coefficient estimate: -0.039, prob.: 0.775) and the government-operated hospitals (govdv; coefficient estimate: 0.237, prob.: 0.231) are not statistically different from zero at a five percent significance

level. Thus, the null hypothesis of no relationship between the tax status of the hospital and its financial statement comparability cannot be rejected.

However, a number of additional control variables in the regression exhibit statistically significant coefficient estimates. These include the proportion of licensed beds allocated to rehabilitation care (pbedrehab; coefficient estimate: 1.226, prob.: 0.001), the proportion of licensed beds allocated to another area of care (pbedoth; coefficient estimate: 3.360, prob.: 0.027), the proportion of total outpatient visits offered at an affiliated clinic (pvisclin; coefficient estimate: -0.803, prob.: 0.006), and the proportion of outpatient visits provided at another location (pvisref; coefficient estimate: -0.847, prob.: 0.005), a clinic's location in HSA 5 (East Bay) (HSA5; coefficient estimate: -0.563, prob.: 0.041), a clinic's location in HSA 9 (Central) (HSA9; coefficient estimate: -0.750, prob.: 0.007), a clinic's location in HSA 11 (Los Angeles) (HSA11; coefficient estimate: -0.550, prob.: 0.013), and a clinic's location in HSA 12 (Inland Counties) (HSA12; coefficient estimate: -0.807, prob.: < 0.001). Interestingly, the magnitudes of these significant coefficient estimates suggest that (holding the effects of the other specified regressors constant) hospitals which allocate greater licensed beds to psychiatric care, and greater licensed beds to all other types of care, exhibit financial statement comparability scores that are much higher in magnitude than hospitals with fewer licensed beds allocated to these areas of care. Similarly, those hospitals which provide a greater proportion of outpatient care at clinics, and in all other avenues of outpatient care, exhibit significantly lower financial statement comparability scores (holding the other specified regressors constant). Lastly, hospitals located in HSAs 5, 9, 11, and 12 exhibit significantly lower financial comparability metrics compared to hospitals located in HSA 14 (San Diego; the omitted category).

The quantile regression is used to predict the 15th and 25th percentiles for z-score(CE_i). Table 5, Panel B presents results predicting the 25th percentile for z-score(CE_i). First, note that the coefficient estimates for the private not-for-profit (npdv; coefficient estimate: -0.156, prob.: 0.073), as well as the coefficient estimate for government-operated hospitals (govdv; coefficient estimate: -0.108, prob.: 0.389), are not statistically different from zero at a five percent significance level. Consistent with the results for the median regression, the null hypothesis of no relationship between profit status and financial statement comparability cannot be rejected at the five percent level.

Table 4. Quantile Regression Analysis [n=282]

Dependent Variable: Z-Score(CE)					
Quantile of Interest:		<i>Median</i>			
<u>Regressor</u>	<u>Coefficient Estimate</u>	<u>Std. Error</u>	<u>t-statistic</u>	<u>Probability</u>	
(Intercept)	0.261	0.999	0.261	0.794	
npdv	-0.039	0.137	-0.286	0.775	
govdv	0.237	0.197	1.201	0.231	
ln(hospfte)	0.041	0.190	0.213	0.831	
pnurfte	-0.446	0.617	-0.723	0.470	
ln(medstaff)	0.120	0.071	1.702	0.090	
ln(licbeds)	0.043	0.310	0.138	0.890	
pstaff	0.591	0.501	1.178	0.240	

pbedpsyc	0.214	0.326	0.657	0.512	
pbedchem	0.717	0.672	1.067	0.287	
pbedrehab	1.226	0.378	3.241	0.001	*
pbedltc	0.362	0.370	0.979	0.328	
pbedoth	3.360	1.511	2.223	0.027	*
ln(tdays)	-0.136	0.231	-0.590	0.556	
pdaycr	-0.022	0.476	-0.047	0.963	
pdaycd	0.005	0.462	0.011	0.991	
pdayoth	0.647	0.431	1.500	0.135	
ln(tvisits)	0.002	0.066	0.030	0.976	
vistotdv	0.310	0.572	0.542	0.588	
pviscr	0.159	0.449	0.354	0.723	
pviscd	0.284	0.412	0.688	0.492	
pvisoth	-0.009	0.592	-0.016	0.987	
pvisclin	-0.803	0.289	-2.776	0.006	*
pvishome	-1.945	1.295	-1.502	0.134	
pvisref	-0.847	0.296	-2.859	0.005	*
ruraldv	-0.367	0.212	-1.731	0.085	
teachdv	-0.128	0.226	-0.567	0.571	
HSA1	-0.527	0.313	-1.686	0.093	
HSA2	-0.038	0.286	-0.132	0.895	
HSA3	-0.101	0.314	-0.322	0.748	
HSA4	-0.108	0.296	-0.365	0.715	
HSA5	-0.563	0.274	-2.057	0.041	*
HSA6	-0.509	0.284	-1.791	0.075	
HSA7	-0.644	0.341	-1.890	0.060	
HSA8	-0.406	0.316	-1.286	0.200	
HSA9	-0.750	0.277	-2.705	0.007	*
HSA10	0.379	0.330	1.146	0.253	
HSA11	-0.550	0.220	-2.508	0.013	*
HSA12	-0.807	0.241	-3.343	< 0.001	*
HSA13	-0.343	0.261	-1.315	0.190	
Pseudo R-square	0.158				
Mean Absolute Error	0.598				

* indicates statistical significance at the 5% level or better

A number of control variables in this regression exhibit statistically significant coefficient estimates. These include the natural logarithm of medical staff (ln(medstaff); coefficient estimate: 0.132; prob.: 0.003), the proportion of licensed beds that are staffed (pstaff; coefficient estimate: 0.733, prob.: 0.022), the proportion of beds assigned to chemical dependency care (pbedchem;

coefficient estimate: 0.896, prob.: 0.037), the proportion of licensed beds allocated to rehabilitation care (pbedrehab; coefficient estimate: 0.671, prob.: 0.006), the proportion of licensed beds allocated to long-term care (pbedltc; coefficient estimate: 0.602, prob.: 0.011), the proportion of beds assigned to another area of care (pbedoth; coefficient estimate: 4.463, prob.: < 0.001), the proportion of outpatient visits conducted in a clinic setting (pvisclin; coefficient estimate: -0.563, prob.: 0.002), and the proportion of visits held in all other settings (pvisref; coefficient estimate: -0.828, prob.: < 0.001). Hospitals located in HSAs 6, 7, 9, 11, and 12 exhibit significantly lower financial comparability metrics compared to hospitals located in HSA 14 (San Diego; the omitted category). Overall, the results of this regression indicate that hospitals with beds allocated towards specialty care services, as well as those located in specific regions of the state, exhibit significantly different financial comparability metrics when compared to their peers.

Next, consider the results predicting the 15th percentile of z-score(CE_i). As in the previous regressions, the coefficient estimates for both the private not-for-profit (coefficient estimate: -0.096, prob.: 0.163) and the government-operated hospitals (coefficient estimate: -0.087, prob.: 0.378) are not statistically different from zero at a five percent significance level. Thus, the null hypothesis of no relationship between the profit status of the hospital and its financial statement comparability, again, cannot be rejected.

A number of control variables exhibit statistically significant parameter estimates. These significant coefficient estimates contain both similarities and differences relative to the previous regressions. For example, the natural logarithm of medical staff (ln(medstaff); coefficient estimate: 0.104; prob.: 0.004), the proportion of licensed beds that are staffed (pstaff; coefficient estimate: 0.837, prob.: 0.001), the proportion of beds assigned to chemical dependency care (pbedchem; coefficient estimate: 1.440, prob.: < 0.001), the proportion of licensed beds allocated to rehabilitation care (pbedrehab; coefficient estimate: 0.794, prob.: < 0.001), and the proportion of beds assigned to another area of care (pbedoth; coefficient estimate: 3.947, prob.: < 0.001) continue to exhibit positive and statistically significant coefficient estimates. However, unlike the previous regression, the proportion of beds allocated to long-term care is not statistically significant at the five percent level. Additionally, the coefficient estimate for the natural logarithm of inpatient days (ln(tdays); coefficient estimate: -0.392; prob.: < 0.001) is now statistically significant, as is the proportion of inpatient days for patients insured by another type of third-party payer (pdayoth; coefficient estimate: 1.106; prob.: < 0.001). Several coefficient estimates for variables describing the outpatient care hospitals provide are also statistically significant at the 5 percent level. These include the proportion of total visits attributed to Medicare patients (pviscr; coefficient estimate: -0.778; prob.: < 0.001), the proportion of outpatient visits conducted in a clinic setting (pvisclin; coefficient estimate: -0.744, prob.: < 0.001), the proportion of outpatient visits provided through the hospital's home care programs (pvishome; coefficient estimate: -1.424; prob.: 0.029), and the proportion of visits held in all other settings (pvisref; coefficient estimate: -0.955, prob.: < 0.001). Lastly, hospitals located in HSAs 2 and 3 exhibited significantly higher financial comparability metrics compared to hospitals located in HSA 14 (San Diego; the omitted category), while hospitals located in HSAs 12 and 13 exhibited significantly lower financial comparability metrics compared to the omitted category. Overall, the results of this regression indicate that hospitals with beds allocated towards specialty care services, as well as those located in specific regions of the state, exhibit significantly different financial comparability metrics compared to their peers. Interestingly, unlike at the 25th percentile, the mix of inpatient services and a wider array of outpatient service variables play a significant role in predicting which hospitals have comparability metrics ranking at the 15th percentile.

Table 6 contains the quantile regression results for the 75th and 85th percentiles for z-score(CE_i), respectively. Table 6, Panel A presents results predicting the 75th percentile for z-score(CE_i). The coefficient estimate for private not-for-profit hospitals (npdv; coefficient estimate: -0.224, prob.: 0.090) remains statistically insignificant at the five percent level. However, the coefficient estimate for government-operated hospitals (govdv; coefficient estimate: 0.396, prob.: 0.038) is now statistically different from zero at a five percent significance level. Thus, the null hypothesis of no relationship between the profit status of the hospital and its financial statement comparability is rejected, particularly for government-operated not-for-profit hospitals.

Table 5. Quantile Regression Analysis [n=282]

Dependent Variable: z-score(CE)										
Panel A						Panel B				
Quantile of Interest:		15th %					25th %			
<u>Regressor</u>	<u>Coefficient Estimate</u>	<u>Std. Error</u>	<u>t-statistic</u>	<u>Probability</u>		<u>Coefficient Estimate</u>	<u>Std. Error</u>	<u>t-statistic</u>	<u>Probability</u>	
(Intercept)	-0.001	0.501	-0.002	0.998		-0.096	0.633	-0.152	0.879	
npdv	-0.096	0.069	-1.399	0.163		-0.156	0.087	-1.800	0.073	
govdv	-0.087	0.099	-0.882	0.378		-0.108	0.125	-0.863	0.389	
ln(hospfte)	0.149	0.095	1.562	0.120		0.026	0.121	0.214	0.831	
pnurfte	0.257	0.309	0.832	0.406		0.106	0.391	0.271	0.786	
ln(medstaff)	0.104	0.035	2.946	0.004	*	0.132	0.045	2.958	0.003	*
ln(licbeds)	0.214	0.155	1.376	0.170		0.048	0.196	0.246	0.806	
pstaff	0.837	0.251	3.329	0.001	*	0.733	0.318	2.307	0.022	*
pbedpsyc	0.223	0.163	1.367	0.173		0.379	0.207	1.835	0.068	
pbedchem	1.440	0.337	4.272	< 0.001	*	0.896	0.426	2.103	0.037	*
pbedrehab	0.794	0.190	4.185	< 0.001	*	0.671	0.240	2.799	0.006	*
pbedltc	0.320	0.186	1.726	0.086		0.602	0.234	2.567	0.011	*
pbedoth	3.947	0.758	5.208	< 0.001	*	4.463	0.958	4.659	< 0.001	*
ln(tdays)	-0.392	0.116	-3.380	< 0.001	*	-0.179	0.147	-1.219	0.224	
pdaycr	0.340	0.239	1.424	0.156		0.187	0.302	0.620	0.536	
pdaycd	0.325	0.232	1.403	0.162		-0.346	0.293	-1.180	0.239	
pdayoth	1.106	0.216	5.118	< 0.001	*	0.470	0.273	1.720	0.087	
ln(tvisits)	0.065	0.033	1.977	0.049	*	0.037	0.042	0.898	0.370	
vistotdv	-0.225	0.287	-0.783	0.434		0.120	0.362	0.331	0.741	
pviscr	-0.778	0.225	-3.456	< 0.001	*	-0.427	0.285	-1.501	0.135	
pviscd	-0.305	0.207	-1.475	0.142		-0.047	0.261	-0.180	0.857	

pvisoth	-0.070	0.297	-0.237	0.813		-0.229	0.375	-0.611	0.542	
pvisclin	-0.744	0.145	-5.125	< 0.001	*	-0.563	0.183	-3.071	0.002	*
pvishome	-1.424	0.649	-2.193	0.029	*	-1.075	0.821	-1.310	0.191	
pvisref	-0.955	0.149	-6.433	< 0.001	*	-0.828	0.188	-4.409	< 0.001	*
ruraldv	-0.036	0.106	-0.336	0.737		-0.076	0.134	-0.564	0.573	
teachdv	0.070	0.113	0.614	0.540		0.195	0.143	1.365	0.174	
HSA1	0.420	0.157	2.681	0.008	*	-0.098	0.198	-0.494	0.622	
HSA2	0.135	0.144	0.944	0.346		0.130	0.181	0.714	0.476	
HSA3	0.420	0.157	2.671	0.008	*	-0.076	0.199	-0.384	0.702	
HSA4	0.135	0.148	0.910	0.364		-0.054	0.187	-0.290	0.772	
HSA5	-0.102	0.137	-0.744	0.458		-0.328	0.174	-1.890	0.060	
HSA6	-0.006	0.143	-0.042	0.966		-0.508	0.180	-2.817	0.005	*
HSA7	-0.282	0.171	-1.650	0.100		-0.466	0.216	-2.158	0.032	*
HSA8	-0.113	0.158	-0.713	0.476		-0.360	0.200	-1.797	0.074	
HSA9	-0.103	0.139	-0.740	0.460		-0.455	0.176	-2.589	0.010	*
HSA10	0.168	0.166	1.013	0.312		-0.203	0.209	-0.968	0.334	
HSA11	-0.074	0.110	-0.670	0.503		-0.368	0.139	-2.645	0.009	*
HSA12	-0.275	0.121	-2.274	0.024	*	-0.492	0.153	-3.214	0.001	*
HSA13	0.269	0.131	2.055	0.041	*	-0.122	0.165	-0.740	0.460	
Pseudo R-square	0.152					0.155				
Mean Absolute Error	0.798					0.690				

* indicates statistical significance at the 5% level or better

Table 6. Quantile Regression Analysis [n=282]

Dependent Variable: z-score(CE)										
Panel A					Panel B					
Quantile of Interest:		75th %					85th %			
<u>Regressor</u>	<u>Coefficient Estimate</u>	<u>Std. Error</u>	<u>t-statistic</u>	<u>Probability</u>		<u>Coefficient Estimate</u>	<u>Std. Error</u>	<u>t-statistic</u>	<u>Probability</u>	
(Intercept)	-0.175	0.960	-0.183	0.855		-0.535	0.996	-0.537	0.592	
npdv	-0.224	0.131	-1.701	0.090		-0.127	0.137	-0.928	0.355	
govdv	0.396	0.190	2.088	0.038	*	0.632	0.197	3.210	0.002	*
ln(hospfte)	0.069	0.183	0.378	0.705		0.220	0.190	1.158	0.248	
pnurfte	-0.178	0.593	-0.300	0.764		0.588	0.615	0.955	0.340	
ln(medstaff)	0.044	0.068	0.655	0.513		0.108	0.070	1.531	0.127	
ln(licbeds)	0.057	0.298	0.193	0.847		-0.215	0.309	-0.695	0.488	
pstaff	0.231	0.482	0.480	0.632		0.264	0.500	0.528	0.598	
pbedpsyc	-0.015	0.313	-0.047	0.962		0.376	0.325	1.156	0.249	
pbedchem	5.141	0.646	7.958	< 0.001	*	5.518	0.671	8.227	< 0.001	*
pbedrehab	1.155	0.363	3.178	0.002	*	1.334	0.377	3.537	< 0.001	*
pbedltc	0.180	0.355	0.507	0.613		0.284	0.369	0.769	0.443	
pbedoth	2.134	1.452	1.469	0.143		2.218	1.508	1.471	0.143	
ln(tdays)	0.019	0.222	0.085	0.932		0.052	0.231	0.227	0.821	
pdaycr	-0.777	0.458	-1.698	0.091		-0.885	0.475	-1.861	0.064	
pdaycd	-0.953	0.444	-2.145	0.033	*	-0.707	0.461	-1.533	0.127	
pdayoth	0.318	0.414	0.769	0.443		0.641	0.430	1.490	0.138	
ln(tvisits)	-0.022	0.063	-0.353	0.724		-0.034	0.066	-0.512	0.609	
vistotdv	0.393	0.549	0.716	0.475		0.346	0.570	0.607	0.545	
pviscr	0.807	0.431	1.872	0.062		1.188	0.448	2.653	0.008	*
pvised	0.927	0.396	2.342	0.020	*	1.458	0.411	3.546	< 0.001	*

pvisoth	0.179	0.568	0.315	0.753		0.062	0.590	0.105	0.917	
pvisclin	-0.953	0.278	-3.429	< 0.001	*	-1.001	0.289	-3.467	< 0.001	*
pvishome	3.450	1.244	2.773	0.006	*	5.950	1.292	4.607	< 0.001	*
pvisref	-1.180	0.285	-4.146	< 0.001	*	-1.096	0.295	-3.709	< 0.001	*
ruraldv	-0.192	0.203	-0.946	0.345		-0.432	0.211	-2.044	0.042	*
teachdv	0.077	0.217	0.356	0.722		0.886	0.225	3.930	< 0.001	*
HSA1	-0.020	0.300	-0.066	0.947		-0.309	0.312	-0.990	0.323	
HSA2	-0.176	0.275	-0.641	0.522		-0.597	0.285	-2.093	0.037	*
HSA3	0.404	0.301	1.340	0.182		-0.070	0.313	-0.224	0.823	
HSA4	1.183	0.284	4.165	< 0.001	*	0.838	0.295	2.843	0.005	*
HSA5	-0.469	0.263	-1.781	0.076		-0.295	0.273	-1.080	0.281	
HSA6	-0.237	0.273	-0.868	0.386		-0.256	0.284	-0.901	0.368	
HSA7	0.183	0.328	0.559	0.577		-0.189	0.340	-0.555	0.579	
HSA8	-0.596	0.304	-1.964	0.051		-0.860	0.315	-2.728	0.007	*
HSA9	-0.574	0.266	-2.155	0.032	*	-1.042	0.276	-3.771	< 0.001	*
HSA10	1.072	0.317	3.377	< 0.001	*	0.689	0.330	2.090	0.038	*
HSA11	-0.129	0.211	-0.610	0.543		-0.516	0.219	-2.357	0.019	*
HSA12	-0.554	0.232	-2.389	0.018	*	-0.772	0.241	-3.209	0.002	*
HSA13	-0.316	0.251	-1.260	0.209		-0.728	0.260	-2.798	0.006	*
Pseudo R-square	0.186					0.253				
Mean Absolute Error	0.808					1.007				

* indicates statistical significance at the 5% level or better

Several control variables exhibit statistically significant coefficient estimates at the five percent level. These include the proportion of beds assigned to chemical dependency care (pbedchem; coefficient estimate: 5.141, prob.: < 0.001), the proportion of licensed beds allocated to rehabilitation care (pbedrehab; coefficient estimate: 1.155, prob.: 0.002), the proportion of inpatient days provided to patients insured by MediCal (pdaycd; coefficient estimate: -0.953; prob.: 0.033), the proportion of outpatient visits for patients insured by MediCal (pviscd; coefficient estimate: 0.927; prob.: 0.020), the proportion of outpatient visits conducted in a clinic setting (pvisclin; coefficient estimate: -0.953, prob.: < 0.001), the proportion of visits provided by hospital home care programs (pvishome; coefficient estimate: 3.450; prob.: 0.006), and the proportion of visits held in all other settings (pvisref; coefficient estimate: -1.180, prob.: < 0.001). Lastly, hospitals located in HSAs 4 and 10 exhibit significantly higher financial comparability metrics compared to hospitals located in HSA 14 (San Diego; the omitted category), while hospitals located in HSAs 9 and 12 exhibit significantly lower financial comparability metrics compared to the omitted category. Once again, hospitals with beds allocated towards specialty care services, as well as those located in specific regions of the state, exhibit significantly different financial comparability metrics compared to their peers. Interestingly, and unlike the previous regression, a reliance on providing services to MediCal patients plays a significant role in predicting which hospitals have financial comparability metrics ranking at the 75th percentile.

Table 6, Panel B presents results predicting the 85th percentile for z-score(CE_i). The coefficient estimate for private not-for-profit hospitals (npdv; coefficient estimate: -0.127, prob.: 0.355) remains not statistically different from zero at the five percent level, while the coefficient estimate for government-operated hospitals (govdv; coefficient estimate: 0.632, prob.: 0.002) is statistically different from zero at a five percent significance level. Once again, the null hypothesis of no relationship between the profit status of the hospital and its financial statement comparability is rejected for government-operated not-for-profit hospitals.

Control variables whose coefficient estimates are statistically significant at the 5 percent level include the following: the proportion of beds assigned to chemical dependency care (pbedchem; coefficient estimate: 5.518, prob.: < 0.001), the proportion of licensed beds allocated to rehabilitation care (pbedrehab; coefficient estimate: 1.334, prob.: < 0.001), the proportion of outpatient visits by Medicare insured patients (pviscr; coefficient estimate: 1.188; prob.: 0.008), the proportion of outpatient visits for patients insured by MediCal (pviscd; coefficient estimate: 1.458; prob.: < 0.001), the proportion of outpatient visits conducted in a clinic setting (pvisclin; coefficient estimate: -1.001, prob.: < 0.001), the proportion of visits provided by hospital home care programs (pvishome; coefficient estimate: 5.950; prob.: 0.006), the proportion of visits held in all other settings (pvisref; coefficient estimate: -1.096, prob.: < 0.001), hospitals located in rural areas (ruraldv; coefficient estimate: -0.432; prob.: 0.042), and hospitals designated as teaching hospitals (teachdv; coefficient estimate: 0.886; prob.: < 0.001). Lastly, hospitals located in HSAs 4 and 10 continue to exhibit significantly higher financial comparability compared to hospitals located in HSA 14 (San Diego; the omitted category), holding the other specified regressors in the model constant. Concomitantly, hospitals located in HSAs 8, 9, 11, 12, and 13 exhibited significantly lower financial comparability metrics compared to the omitted category. Hospitals with beds allocated towards specialty care services, those hospitals that provided additional outpatient services, as well as those located in specific regions of the state, exhibit significantly different financial comparability metrics compared to their peers.

Discussion and Conclusions

The goal of this study was to empirically assess whether the financial accounting statements of hospitals with different tax statuses are systematically comparable. The results of the analysis are threefold. First, when evaluating firms at the sample median, the 25th percentile, or the 15th percentile, no statistically significant differences in financial statement comparability exist across hospitals with different tax statuses. However, when evaluating the 75th and 85th percentiles, government-operated, not-for-profit hospitals exhibited statistically higher financial comparability measures compared to other types of firms (holding the other specified regressions in the model constant). Higher scores simply mean that government-operated hospitals are more likely to be “outliers” and exhibit fundamentally different, and less comparable, information in their financial statements relative to their peers.

Second, a number of variables describing the infrastructure of each hospital, including the array of services provided and the distribution of patients who are served by a hospital, significantly predict financial statement comparability. The results suggest the provision of rehabilitation and chemical dependency care, in particular, influences the comparability of firms in the sample. This result should not be surprising. The mix of services provided, the patients who utilize those services, and the generosity with which hospitals are reimbursed for providing those services, determine a hospital’s financial position. Hospitals that provide an array of different services have different potentials to expand current resources and generate new resources. These differences would be evident on their financial statements and those firms would look different to analysts.

A caveat to this finding is that the set of hospital-specific characteristics that influences financial statement comparability changes (sometimes markedly) with the percentile of the financial statement comparability measure. Hospitals that exhibit very high or very low financial statement comparability metrics have a different set of factors which significantly predict comparability, compared to the median hospital. In other words, the sample of hospitals is not homogeneous, and the researcher is advised to first determine whether the goal is to identify “similar” firms at the center of the distribution, or whether one is trying to predict “outlying” firms who are fundamentally different from others in the data set. The results of this study suggest that those two inquiries are fundamentally distinct.

A third finding of this study is that financial statement comparability varies significantly by health services area (HSA). Hospitals are intentionally designed to serve as part of a social safety net for their communities and alter their operations to meet the needs of the communities they serve. These community-specific factors significantly alter the financial statements of hospitals, impacting their comparability to other hospitals in the state. Additionally, the impact of HSA location on financial statement comparability depends critically on the sample percentile examined. Hospital comparability depends on whether one is assessing the middle of the distribution (i.e., examining the “average” financial statement comparability of these hospitals) or the extreme ends of the distribution (i.e., examining the data and assessing “outliers”). These two inquiries are fundamentally different exercises.

This study has numerous implications for managers and policymakers. Not all financial statements from hospitals in the sample are comparable. This is due to a variety of factors, including tax status, the productive capacities of the firm, and the socio-economic and epidemiologic conditions within which hospitals operate. When benchmarking hospital financial performance, one must either select peers very carefully, taking into account all of the above factors, or control for each of these factors when assessing financial statement comparability.

Managers and policymakers must also determine whether they want to assess financial statement comparability by examining which peers are “similar” to each other, versus which hospitals are “distinct”. In all circumstances, selecting peers when benchmarking hospital financial performance is a very nuanced endeavor that must be implemented with a high degree of institutional knowledge and careful planning.

While the results of this analysis present some interesting findings, they are subject to a number of limitations. The data are drawn from a single year (2022) and a single state (California). Replications of this study using data drawn from other geographic regions and other time frames may yield disparate results. In addition, this analysis assesses financial statement comparability using data drawn from the income statement and the balance sheet. Replications of this study that utilize a broader array of financial statement information, possibly drawn from additional financial statements, may generate different assessments of financial statement comparability that improve upon those identified here. Next, the results are dependent on the assumption that firms operate in a mixed competitive market. If that is not the case, the results of the analysis may change. If the market is comprised solely of for-profit firms, alternative means to characterize financial statement comparability may be available. Those alternative measures may yield different, or additional, inferences not addressed in the current study. Lastly, the study utilizes a reduced-form, linear-in-parameters regression specification to generate estimates. If that specification is not consistent with actual production, or if critical variables are not included in the specification, the results of this study may be biased. Future research that addresses each of these limitations would provide a valuable contribution to the literature.

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