Does Service Mix or Payer Mix Matter More in Peer Formation? Empirical Evidence from Primary Care Community Clinics

Daniel L. Friesner
University of Akron

Andrew Brajcich
Gonzaga University

Matthew Q. McPherson
Gonzaga University

A financial statement comparability-based benchmarking analysis is undertaken to empirically assess whether a health care organization's service mix, or its patient mix (as defined by a patient's primary insurer) matter relatively more in the formation of peers. Data for the study are drawn from primary care community clinics (PCCCs) operating in the State of California in 2022. Our findings are twofold. First, both patient mix and service mix characteristics under the PCCC's control significantly impact financial statement comparability, and account for as much as 40 percent of the formation of financial statement comparability peer rankings. Second, differences in payer mix across firms are more likely than service mix differences in determining the closeness of PCCCs peers.

Keywords: financial statement comparability, primary care community clinics, service mix, payer mix, not-for-profit firms

INTRODUCTION AND LITERATURE REVIEW

Assessing the financial performance of an organization, relative to peers, is a critical aspect of evaluating the success or failure of an organization (Do, 2021). A variety of factors make this challenging in the healthcare industry. Healthcare organizations are multi-output producers (Hollingsworth, 2008). They differ in the scope, complexity, and mix of services offered (Sinay, 2008). Reimbursement for services (the organization's primary revenue streams) is often dictated by the mix of patients served by the firm, and more specifically, the insurers responsible for covering the majority of the firm's patients (a payer mix) (Hassan et al., 2008). Lastly, many firms differ in their missions, operating objectives, and legal organization (including tax status), making the consistent interpret of information drawn from firm financial statements difficult (Moon & Shugan, 2020). Perhaps more problematic, health care organizations are extremely heterogeneous; they may exhibit similarities in one or two of these areas, but not in all of them (Hollingsworth, 2008; Horwitz & Nichols, 2011).

A common approach in such circumstances is to benchmark the financial performance of the organization against a subset of organizations in a region or a market (or both) based on these qualifying characteristics (Panagiotou, 2007). For example, an organization may be benchmarked against *only* those organizations that have a similar tax status, that offer a similar collection of services (service mix), or that have a similar payer mix. This is problematic for several reasons. First, this type of benchmarking *presumes* that these qualifying factors are individually and collectively important in peer selection. If more than one characteristic is used to designate possible peers, the relative importance of these characteristics is critical in the identification of peers. Additionally, some qualifications, especially payer mix, are not directly under the control of the firm, while other characteristics, such as service mix, may (at least partly) be under the control of an organization. The former would likely change in a predictable and exogenous manner over time, leading to a stable set of peers. The latter may lead to more dramatic changes in peer groups, as well as changes in benchmarks against one's peers over time (Friesner & Brajcich, 2023). To date, few studies within the healthcare finance and accounting literatures have assessed the relative importance of payer mix and service mix in the benchmarking of an organization against objectively-defined peers groups.

Through a simple financial statement comparability-based benchmarking analysis, this study empirically addresses whether and how service mix and payer mix contribute useful information in the identification of peers. The remainder of this paper proceed as follows. In section 2, the empirical methods used to assess financial statement comparability are described. The third section describes the data, which are drawn from a sample of not-for-profit, primary care community clinics (PCCCs) operating in the State of California in 2022. The fourth section contains the empirical results. The paper concludes by summarizing findings, identifying implications for management and policy, and identifying suggestions for future research.

EMPIRICAL METHODOLOGY

Our empirical methodology is adapted from Friesner, Brajcich, Friesner, and McPherson (2025), which presents a constrained quadratic programming problem (based on information entropy theory) to assess financial statement comparability across a group of critical access hospitals. Information entropy methods were selected over other alternatives (for example, De Franco, Kothari, & Verdi (2011) and Hoitash, Hoitash, Kurt, & Verdi (2023)), as they allow for the inclusion of organizations that may not have a strictly profit or wealth-maximizing objective. In addition, information entropy methods allows for the inclusion of both (objectively reported) financial statement information and (potentially non-financial) operating characteristics.

The Friesner et al. (2025) methodology assumes that the researcher has access to a series of $l = 1,\dots,L$ variables that are consistently, accurately, and precisely collected over a sample of $i = 1,\dots,n$ firms. At least one of the L variables is drawn from a financial statement. Each of the L variables should be expressed in common form. The number of mutually exclusive and collectively exhaustive categories into which a particular variable can be disaggregated may vary from one variable to the next. Suppose that the first variable (for example, firm assets) can be disaggregated into $j = 1,\dots,J$ categories (cash, net property, plant and equipment, etc.). Let q_{ij} be the proportion of financial resources for variable 1 that firm i allocated to the j^{th} category; and p_j is the optimal industry benchmark across all $i=1,..,n$ firms for the j^{th} proportion. Notation for the other L-1 variables is defined analogously. Friesner et al. (2025) propose to choose the industry benchmarks in a manner that minimizes cross-entropy across all L variables:

$$min_{p_1,\dots,p_J,\rho_1,\dots,\rho_K,\dots,\omega_1,\dots,\omega_H} \sum_{i=1}^{n} CE_i = \sum_{i=1}^{n}\left(\sum_{j=1}^{J} p_j log_2\left(\frac{p_j}{q_{ij}}\right) + \sum_{k=1}^{K} \rho_k log_2\left(\frac{\rho_k}{r_{ik}}\right) + \cdots + \sum_{h=1}^{H} \omega_h log_2\left(\frac{\omega_h}{w_{ih}}\right)\right) \quad (1)$$

Subject to:

$p_j \geq 0 \; \forall \; j = 1, \dots, J;$

$p_j \leq 1 \; \forall \; j = 1, \dots, J;$

$\rho_k \geq 0 \; \forall \; k = 1, \dots, K;$

$\rho_k \leq 1 \; \forall \; k = 1, \dots, K;$

$\vdots$

$\omega_h \geq 0 \; \forall \; h = 1, \dots, H;$

$\omega_h \leq 1 \; \forall \; h = 1, \dots, H$

$\sum_{j=1}^{J} p_j = 1$

$\sum_{k=1}^{K} \rho_k = 1$

$\vdots$

$\sum_{h=1}^{H} \omega_h = 1$

The formation described in (1) generates an optimal solution that can be used to identify groups of organizations which exhibit relatively similar (or divergent) information in their financial statements. As a rough heuristic guideline, firms whose cross-entropy measures (CE_i) are more than two standard deviations from the mean (or whose z-score transformed CE_i measures are greater than two in absolute value) are likely to be non-comparable to firms whose cross entropy measures (CE_i) are close to the mean.

We assume that data may be drawn from a collection of PCCCs that approximate a randomly collected sample. The data must include financial statement information, as well as information representing payer mix and service mix, for each PCCC. Therefore, the operationalization of equation (1) has at least three distinct sets of terms in the objective function. Following Friesner et al. (2024) we operate under the (conservative) null hypothesis that neither payer mix nor service mix significantly impact the formation of peer groups. As such, estimating a restricted model where one or both sets of information are eliminated should not substantively change the relative positioning of firms (as measured by rank ordering of CE_i scores) in the dataset compared to an unrestricted model where both payer mix and service mix are included. The study's hypotheses are formalized via the following:

$\boldsymbol{H_0}$*: No mean/median differences exist in* CE_i *across restricted and unrestricted models.*

$\boldsymbol{H_A}$: *Not* H_0

Because the objective function in (1) is additive, eliminating one full set of summed terms from the unrestricted model does not impact the optimally imputed values for any other set of variables in the model. Thus, the null hypothesis can be evaluated by estimating the fully unrestricted model and calculating the CE_i scores. Restricted models can be evaluated by recalculating CE_i scores excluding the set of terms comprising the restriction. Wilcoxon signed rank tests and median sign tests can be used to assess H_0 versus H_A, both for payer mix and service mix.

Should the null hypothesis be rejected for both payer mix and service mix, the relative importance of each in the formation of peer groups can be determined. To evaluate this issue, Friesner et al. (2025) recommend applying bivariate Spearman (nonparametric) correlations to assess the relationship between the unrestricted model and i) a "fully restricted" model where both payer and service mix variables are excluded; ii) a "partially restricted" model where only payer mix is excluded; and iii) a "partially restricted" model where only service mix variables are excluded. The *more highly correlated* a particular restricted model is with the fully unrestricted model, the *less unique information* the restriction contributes to the formation of peer groups and financial statement comparability. This is because the relative rankings of firms are unlikely to change regardless of whether the information contained in the restriction is included or excluded from the model.[1]

DATA

Data consist of PCCCs who operated in California during the 2022 calendar year. These PCCCs are either hold for-profit or not-for-profit legal tax status. All PCCCs operating in the state are required to disclose a full set of financial, operating, and service mix variables to the California Office of Health care Access and Information (HCAI) on an annual basis. These data are audited, cleaned and made publicly available (https://hcai.ca.gov/data/datasets/).[2]

There were 1,250 clinics operating in the state in 2022. Of these clinics, 88 did not operate a full year, 41 were "free" clinics that neither collected nor reported revenues, and 136 did not report other information required for the analysis. Eliminating these clinics left a working sample of 985 observations (78.8 percent of the original sample).

The income statement serves as the primary source of financial statement information. Revenues (net of discounts and contractual adjustments) are reported and disaggregated into five mutually exclusive and collectively exhaustive business type categories: Medicare & Medicare Managed Care; MediCal (Californian's Medicaid program)/MediCal Managed Care; private insurers; all other insurers; and non-patient care revenue sources. Expenses are placed into nine mutually exclusive and collectively exhaustive categories: salary, wage, and employee benefit expenses; professional contract services; medical and dental supplies; office and other supplies; expenses from outside patient care services; rent, depreciation, and mortgage interest expenses; utilities; professional liability and other types of insurance; and all other expenses.

Information on the staffing (on a full-time equivalent employee basis) at each PCCC provides critical information on each clinic's productive capabilities. Providers were disaggregated into two (mutually exclusive and collectively exhaustive) groups: employees with and without provider status. Providers include the following categories: Non-psychiatric physicians; physician extenders (physician assistants, nurse practitioners, etc.); dentists and advanced practice dental hygienists; psychiatrists and clinical psychologists; social workers; and all other types of providers. Non-provider staff include registered nurses, administrative staff, medical assistants, and all other non-provider staff.

Lastly, data are available to characterize the mix of services provided at each PCCC. Services were classified into one of ten mutually exclusive and collectively exhaustive categories based on the primary CPT code for each patient encounter: new patient evaluations & management, previous patient evaluations & management, infant and child preventive care, adult preventive care, respiratory or cardiovascular care, (male or female) reproductive care and maternity care, pathology, specialty medical services, dental care, and all other types of patient care services.

RESULTS

Table 1 contains the variable names, descriptions, and descriptive statistics for each of the variables used in the analysis (all variables are evaluated at the mean). The typical clinic generates approximately \$8.16 million in revenues, the vast majority of which come from serving Medicaid/Medicaid Managed Care insured patients and from non-patient care sources. The latter are gained through the receipt of grants, donations and other related sources. The typical PCCC incurs approximately \$7.72 million dollars in expenses, the majority of which are attributed to labor-related expenses. Revenues only slightly exceed expenses, and there is considerable variation across PCCCs in both revenues and expenses. PCCCs employ approximately 9.381 FTEs with provider status, the majority of whom are physicians or physician extenders. Similarly, PCCCs employ approximately 34.936 non-provider FTEs, of whom 41.6 percent are administrative staff and 31.5 percent are medical assistants. Lastly, the mean PCCC provides 23,372.260 patient encounters each year, of which 55.2 percent is devoted to new patient evaluations and management. The standard deviation for patient encounters (28,548.766) is very large, implying that PCCCs have considerable variation in size and scope of care. The large number of patient encounters devoted to new patient evaluations and management indicate that PCCCs play a critical role in providing ambulatory services to their communities.

TABLE 1
DESCRIPTIVE STATISTICE [N=985]

Variable	Definition	Mean	Std. Dev.
Clinic Revenues			
TPREV	Total operating revenue	$8,164,819.37	$11,984,040.56
pmcare	Proportion of clinic revenues derived from treating Medicare/Medicare Managed Care patients	0.062	0.098
pmcal	Proportion of clinic revenues derived from treating Medicaid/Medicaid Managed Care patients	0.477	0.258
ppvt	Proportion of clinic revenues derived from treating privately insured patients	0.055	0.102
pothrev	Proportion of clinic revenues derived from treating all other patients	0.097	0.192
pnonop	Proportion of clinic revenues derived from non-patient care sources	0.310	0.276
Clinic Expenses			
TEXP	Total operating expenses	$7,723,863.94	$10,685,227.40
psalexp	Proportion of total operating expenses from salaries, wages, and employee benefits	0.607	0.159
pcsexp	Proportion of total operating expenses from professional contract services	0.062	0.094
pmsupexp	Proportion of total operating expenses from medical and dental supplies	0.059	0.063
posupexp	Proportion of total operating expenses from office and other supplies	0.009	0.015
poutexp	Proportion of total operating expenses from outside patient care services	0.027	0.075
pcapexp	Proportion of total operating expenses from rent, depreciation, and mortgage interest	0.060	0.052
putilexp	Proportion of total operating expenses from utilities	0.016	0.014
pinsexp	Proportion of total operating expenses from professional liability and other types of insurance	0.008	0.014
pothexp	Proportion of total operating expenses from all other activities	0.152	0.121
Provider FTEs			
TPFTE	Total provider FTEs	9.381	11.593
pmd	Proportion of providers who are (non-psychiatric) MDs	0.327	0.263
pmid	Proportion of providers who are physician extenders (Pas, APRNs, etc.)	0.350	0.279
pddsdh	Proportion of providers who are dentists or dental hygienists	0.129	0.238

pmdpsy	Proportion of providers who are psychiatrists or clinical psychologists	0.026	0.079
plcsw	Proportion of providers who are social workers	0.060	0.100
pothprov	Proportion of providers who are another type of provider	0.107	0.174
Non-Provider Staff FTEs			
TSFTE	Total staff FTEs	34.936	53.551
prn	Proportion of staff who are registered nurses	0.073	0.184
padm	Proportion of staff who are primarily administrative in nature	0.416	0.243
pma	Proportion of staff who are medical assistants	0.315	0.261
pothstaff	Proportion of staff who fill an alternative role	0.196	0.225
Patient Encounters and Service Mix			
TENC	Total patient encounters	23372.260	28548.766
peval	Proportion of patient encounters with a primary CPT code related to new patient evaluations & management	0.552	0.276
pprevi	Proportion of patient encounters with a primary CPT code related to previous patient evaluations & management	0.035	0.055
ppreva	Proportion of patient encounters with a primary CPT code related to infant & child preventive care	0.020	0.029
pinteg	Proportion of patient encounters with a primary CPT code related to adult preventive care	0.008	0.038
prespcard	Proportion of patient encounters with a primary CPT code related to respiratory or cardiovascular conditions	0.009	0.032
preprod	Proportion of patient encounters with a primary CPT code related to (male or female) reproductive care and maternity care	0.014	0.084
ppath	Proportion of patient encounters with a primary CPT code related to pathology	0.023	0.059
pmedspec	Proportion of patient encounters with a primary CPT code related to specialty medical services	0.077	0.120
pdnt	Proportion of patient encounters with a primary CPT code related to dental care	0.087	0.201
poth	Proportion of patient encounters with a primary CPT code related to all other patient care	0.175	0.212

Table 2 presents the results of the optimization problems Each imputed value represents an industry benchmark for PCCCs in the dataset. For most of the common form variables, the optimal benchmarks are relatively close in magnitude to the corresponding sample means presented in Table 1.[3] This implies that PCCCs whose revenues, expenses, employee FTEs, and service mix variables are (when considered jointly) close to the sample means, are likely to be relatively close peers, and have financial statements whose information is comparable to the rest of the peer group. PCCCs whose proportions differ markedly from both the sample means and these optimal benchmarks are less likely to be peers with those whose values do match the mean and/or optimal benchmarks (and are less likely to exhibit financial statement comparability).

Table 2 also reports the overall entropy objective metric for each of the unrestricted and restricted models. This metric is essentially the summation of CE_i values across all firms in the sample. The greater the difference in an overall entropy objective's value between a restricted model and the fully unrestricted model suggests (but does not prove) that the restriction alters the rank ordering of firms in the dataset, which also changes both the identification of peer groups and a PCCCs' financial statement comparability. The overall entropy objective for the unrestricted model is 945.482. The overall entropy objective for the fully restricted model (where both payer mix and service mix are excluded) is 199.760. For restricted model where only payer information is excluded, 480.476, and for the restricted model in which only service mix is restricted, 664.757. Considered collectively, this suggests that both payer mix and service mix contribute to the formation of peer groups and financial statement comparability. However, the exclusion of payer mix information (since its objective value is much lower than that for the restricted model in which only service mix is excluded) appears to more fundamentally alter the formation of peer groups.

TABLE 2
FINANCIAL STATEMENT COMPARABILITY RESULTS [N=985]

			Restricted Model	***Restricted Model***
	Unrestricted Model	***Fully Restricted Model***	***Payer Information Excluded***	***Service Mix Information Excluded***
Variable	**Optimal Pj**	**Optimal Pj**	**Optimal Pj**	**Optimal Pj**
Clinic Revenues				
pmcare	0.057	-	-	0.057
pmcal	0.594	-	-	0.594
ppvt	0.035	-	-	0.035
pothrev	0.047	-	-	0.047
pnonop	0.267	-	-	0.267
Clinic Expenses				
psalexp	0.684	0.684	0.684	0.684
pcsexp	0.036	0.036	0.036	0.036
pmsupexp	0.047	0.047	0.047	0.047
posupexp	0.007	0.007	0.007	0.007
poutexp	0.024	0.024	0.024	0.024
pcapexp	0.052	0.052	0.052	0.052
putilexp	0.015	0.015	0.015	0.015
pinsexp	0.008	0.008	0.008	0.008
pothexp	0.127	0.127	0.127	0.127
Provider FTEs				
pmd	0.194	0.194	0.194	0.194
pmid	0.221	0.221	0.221	0.221
pddsdh	0.245	0.245	0.245	0.245

pmdpsy	0.094	0.094	0.094	0.094
plcsw	0.110	0.110	0.110	0.110
pothprov	0.136	0.136	0.136	0.136
Non-Provider Staff FTEs				
prn	0.117	0.117	0.117	0.117
padm	0.411	0.411	0.411	0.411
pma	0.303	0.303	0.303	0.303
pothstaff	0.169	0.169	0.169	0.169
Service Mix				
peval	0.580	-	0.580	-
pprevi	0.000	-	0.000	-
ppreva	0.016	-	0.016	-
pinteg	0.004	-	0.004	-
prespcard	0.012	-	0.012	-
preprod	0.007	-	0.007	-
ppath	0.012	-	0.012	-
pmedspec	0.060	-	0.060	-
pdnt	0.202	-	0.202	-
poth	0.107	-	0.107	-
Overall Entropy Objective	945.482	199.760	480.476	664.757

Table 3, Panel A contains descriptive statistics for the CE_i measure for each of the models. To aid in the identification of possible outliers (who would not be considered peers of the remaining PCCCs in the dataset), the z-score of each CE_i metric is also provided in this panel. The distributions of all models are right skewed, with minimum values well below 2 standard deviations from the mean. However, the upper half of the distribution – particularly the upper quartile – exhibits very large values well beyond two standard deviations from the mean. The maximum values in the dataset also vary considerably (between 7.650 standard deviations above the mean to 10.900 standard deviations above the mean) between the unrestricted and restricted models. As with the results in Table 2, excluding both service mix and payer mix leads to the largest maximum values (i.e., PCCCs who are not peers with the others in the dataset), while eliminating only payer mix variables leads to maximum CE_i values that are similar to those of the unrestricted model. Wilcoxon signed rank tests and median sign tests reject the null hypothesis of equality between the unrestricted model and each of the restricted models at the 5 percent significance level.

TABLE 3
NONPARAMETRIC ANALYSIS [N=985]

Panel A: Distribution of the Cross-Entropy Scores							
Variable	**Mean**	**Std. Dev.**	**Min.**	**25th %**	**Median**	**75th %**	**Max.**
Unrestricted Model Cross Entropy	0.960	1.425	-1.993	0.158	0.803	1.580	11.861
Fully Restricted Model Cross Entropy	0.203	0.857	-1.270	-0.321	0.111	0.505	8.878

Restricted Model - Payer Information Excluded Cross Entropy	0.488	1.156	-1.532	-0.242	0.351	0.989	9.450
Restricted Model - Service Mix Information Excluded Cross Entropy	0.675	1.212	-1.538	-0.024	0.480	1.086	10.900
Z-Score (Unrestricted Model Cross Entropy)	0.000	1.000	-2.072	-0.563	-0.110	0.435	7.650
Z-Score (Fully Restricted Model Cross Entropy)	0.000	1.000	-1.719	-0.612	-0.107	0.353	10.128
Z-Score (Restricted Model - Payer Information Excluded Cross Entropy)	0.000	1.000	-1.748	-0.632	-0.119	0.434	7.757
Z-Score (Restricted Model - Service Mix Information Excluded Cross Entropy)	0.000	1.000	-1.825	-0.577	-0.161	0.340	8.435
Panel B: Tests for Model Restrictions on Cross Entropy	**Stat.**	**Prob.**	**Positive Differences**	**Negative Differences**			
Median Sign Test							
Unrestricted Model - Fully Restricted Model	20.265	< 0.001	811	174			
Unrestricted Model - Payer Information Excluded Model	23.323	< 0.001	859	126			
Unrestricted Model - Service Mix Information Excluded Model	7.853	< 0.001	612	373			
Payer Information Excluded Model - Fully Restricted Model	7.853	< 0.001	612	373			
Service Mix Information Excluded Model - Fully Restricted Model	23.323	< 0.001	859	126			

Related Samples Wilcoxon Signed-Rank Test							
Unrestricted Model versus Fully Restricted Model	21.041	< 0.001	811	174			
Unrestricted Model versus Payer Information Excluded Model	20.540	< 0.001	859	126			
Unrestricted Model - Service Mix Information Excluded Model	11.836	< 0.001	612	373			
Payer Information Excluded Model versus Fully Restricted Model	11.836	< 0.001	612	373			
Service Mix Information Excluded Model versus Fully Restricted Model	20.540	< 0.001	859	126			

Lastly, Table 4 contains a matrix of spearman correlations across the unrestricted and restricted models. Each of these correlations is statistically significant at a 5 percent level or better. The Spearman correlation between the unrestricted and fully restricted models is 0.600. This implies that jointly restricting payer mix and service mix leads to the greatest information loss (at nearly 40%), and that when considered jointly, both variables add important information to the formation of peers and the determination of whether a PCCC's financial statements are comparable to other PCCCs. The correlation between the unrestricted model and the restricted model where only payer information is excluded is next lowest at 0.774, while the correlation between the unrestricted model and the restricted model where service mix is excluded is the highest, at 0.841. Interestingly the correlation between the restricted model where service mix is excluded and the restricted model where payer mix is excluded is only 0.520. This relatively low correlation implies that both payer mix and service mix provide unique information to the identification of peer groups and financial statement comparability.

TABLE 4
NONPARAMETRIC (SPEARMAN) CORRELATIONS [N=985]

Model	Unrestricted Model Cross Entropy	Fully Restricted Model Cross Entropy	Restricted Model - Payer Information Excluded Cross Entropy	Restricted Model - Service Mix Information Excluded Cross Entropy
Unrestricted Model Cross Entropy	-	0.600	0.774	0.841
Fully Restricted Model Cross Entropy	0.600	-	0.792	0.668
Restricted Model - Payer Information Excluded Cross Entropy	0.774	0.792	-	0.520
Restricted Model - Service Mix Information Excluded Cross Entropy	0.841	0.668	0.520	-

Note: All correlations in Table 4 are statistically significant at the 0.05 level or better using 2-tailed tests.

CONCLUSIONS

The findings of the analysis are threefold. First, both payer mix and service mix contribute to the identification of peer groups and the formation of financial statement comparability in PCCCs. That is, a PCCC seeking to identify its peers should consider financial information (drawn from an income statement), as well as information on payer mix and service mix. Second, while both payer mix and service mix are important in the identification of peers, payer mix matters relatively more than service mix in this process. The Spearman correlation analysis suggests that excluding service mix variables leads to approximately a 15.9% reduction in the amount of information used to create financial statement comparability. and excluding payer mix leads to a 22.6% reduction. Third, in each model estimated, not every PCCC in the sample was considered a peer. Rather a number PCCCs exhibited extremely high information entropy scores, and are identified as “outliers” and are not comparable to the rest of the group. Thus, a failure to conduct financial statement comparability analysis, or the application of ad hoc guidelines for the identification of peers, may lead to comparing clinics that are truly “apples to oranges”.

The study provides some interesting results. However, there are several limitations which make results preliminary in nature. The analysis was limited to financial information drawn from the income statement. While this may be appropriate for PCCCs that are relatively small in both assets/liabilities and scope of services, this may not be appropriate for larger organizations (such as hospitals) which accumulate substantial assets/liabilities. Analysis for the latter may require the inclusion of additional financial statement information to appropriately identify peer groups. Additionally, the inclusion of additional variables that more precisely quantify an organization’s operating objectives may lead to different results. Lastly, the analysis utilized methods that, while consistent with the literature, are nonetheless extremely parsimonious. A re-examination of the paper’s objectives using more complex empirical methods (for example, non-parametric regression or quantile regression) may lead to more nuanced findings.

ENDNOTES

1. All hypothesis tests use a 5% significance level and are conducted using IBM Statistics Version 29.
2. Because the data are freely available to the public and utilize the clinic (not an individual) as the unit of observation, the study is not considered human subjects research.
3. There are a small number of exceptions to this statement. For example, the optimal benchmarks for non-psychiatric physicians and physician extenders (0.221 and 0.194, respectively) are substantially lower than the corresponding sample proportions (0.350 and 0.327, respectively). Concomitantly, the benchmarks for the other provider FTEs (particularly dentists and advanced practice dental hygienists) are higher than their corresponding sample means.

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