Community Health Center Efficiency: The Role of Grant Revenues in Health Center Efficiency

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Abstract:

Objective: To test the relationship between external environments, organizational characteristics, and technical efficiency in federally qualified health centers (FQHCs). We tested the relationship between grant revenue and technical efficiency in FQHCs.

Data Sources/Study Design: Secondary data were collected in each year from the Uniform Data System (UDS) on 644 eligible U.S.-based FQHCs between 2005 and 2007. The study employs a retrospective longitudinal cohort design with instrumental variables.

Principal Findings: Increased grant revenues did not increase the probability that a health center would be on the efficiency frontier. However, increased grant revenues had a negative association with technical efficiency for health centers that were not fully efficient.

Conclusion: If all health centers were operating efficiently, anywhere from 39 to 45 million patient encounters could have been delivered instead of the actual total of 29 million in 2007. Policy makers should consider tying grant revenues to performance indicators, and future work is needed to understand the mechanisms through which diseconomies of scale are present in FQHCs.

Keywords: Efficiency | grants | FQHCs | primary care | health reform

Article:

Federally qualified health centers (FQHCs) were established to provide accessible, affordable, and high-quality health care for all (Lefkowitz 2007; Mass League 2011). FQHCs are nonprofit or private clinics that are located in medically underserved communities or in other locations where they provide care for medically underserved populations. They provide care regardless of patients' ability to pay, offering a sliding fee scale for the poor and uninsured, and are governed by a board that is comprised of a majority of members who are also health center patients (94th U.S. Congress 1975). They grew from a two-site demonstration in the 1960s to the largest primary care network in the United States with over 6,500 sites (Mass League 2011). In 2010, FQHCs served more than 19 million patients and have established themselves as a critical provider of health care for the nation's most vulnerable people. In 2010, the Patient Protection and Affordable Care Act (ACA) provided FQHCs an additional $11 billion over the next 5 years, and they are expected to double their covered population by 2015 (Arvantes 2010; Katz et al. 2011; Kotelchuck, Lowenstein, and Tobin 2011). Now, more than 1 of every 17 Americans receives care in these centers. Although the importance of these centers is without question, evidence is lacking regarding their efficiency in delivering care.

To examine the determinants of technical efficiency in FQHCs, a theoretical framework was developed using resource dependence theory. Resource dependence theory explains the relationship between organizational efficiency and the dependence on external payers (Pfeffer and Salancik 2003). In the case of FQHCs, the two dominant external actors are Medicaid and both federal- and state-level grants. The relationship between external environments and efficiency will be examined empirically in the context of FQHCs.

Data Envelopment Analysis

Data envelopment analysis (DEA) is a mathematical programming technique that envelops the input and output data with a nonparametric production frontier (Cooper, Seiford, and Zhu 2004). DEA identifies top performers in relation to less effective performers (Charnes, Cooper, and Rhodes 1978; Cooper, Seiford, and Zhu 2004). It analyzes multiple inputs and outputs to create a relative efficiency frontier and estimates a single summary measure of efficiency without prior weights (Cooper, Seiford, and Zhu 2004). For each health center, DEA seeks to maximize the weighted outputs over weighted inputs subject to the constraint that the ratio cannot exceed unity (Fulton, Lasdon, and McDaniel 2007). The nonparametric efficiency frontier identifies the most efficient health centers and assigns them a score of 1 (Milliken et al.2011). Thus, the efficiency score for the remaining health centers is a relative measure benchmarked against the most efficient health centers. The ability to analyze multiple inputs and outputs is more aligned with the actual clinical production process (Chilingerian 1995). We chose not to bootstrap the DEA scores due to limitations noted by Tziogkidis (2012).

Whereas limited research has suggested that FQHCs have comparable or lower costs compared to other sources of care, decrease preventable hospitalizations, and provide similar quality of care to physician offices and hospital outpatient departments, there is very little knowledge about the variation in efficiency among FQHCs (Epstein 2001; Falik et al. 2001, 2006; Rosko 2001; Ku, Richard, and Dor 2009; Probst, Laditka, and Laditka 2009; Gurewich et al. 2011; Rothkopf et al. 2011). There is limited evidence that increased reliance on grant funding leads to decreased efficiency (Rosko 2001; Martin, Shi, and Ward 2009). This aligns with x-inefficiency theory, which says that inefficiency occurs when technical efficiency is not being achieved due to lack of competitive pressures (Leibenstein 1966; Leibenstein and Maital 1992). However, the empirical evidence for the relation between grant funding and efficiency is weak. This study uses instrumental variables to explore this relationship further and provide more reliable estimates that do not suffer from possible reverse causality or measurement error (Chernew, Cutler, and Keenan 2005). Technical efficiency as it is defined in this study is the ability to produce maximum output from the chosen combination of inputs.

The increased pressure to double the capacity of FQHCs in the coming years and the limited evidence base on technical efficiency in FQHCs make it unclear whether FQHCs will be able to meet expectations. This research examines the impact of the reliance on grant funding on efficiency in FQHCs and provides an evidence base for policy makers to consider as they seek to double the capacity of these facilities in the near future.

Methods

Variable of Interest

The independent variable of interest was identified from current literature and has a hypothesized negative effect on health center efficiency. The percentage of total revenue that came from grants was 46 percent and represented almost half of the average health centers' income. Grant funding is potentially endogenous with efficiency; thus, the following analyses will employ instrumental variables (IVs). Table 1 displays the mean value for grant dependence and its growth rate over time.

Table 1. Grant Dependence, Growth by Year

	2005	**2006**	**Δ05–06**	**2007**	**Δ06–07**
T. grant rev (%)	0.47	0.45	−5.4%	0.45	1.8%

Unit of Analysis

The unit of analysis for the study is the combined service delivery sites of each FQHC listed in the UDS. One FQHC may have multiple sites of delivery, but the data from all these sites are aggregated and reported at the FQHC level in the UDS. Service delivery sites of health centers are defined as places providing clinical services to a defined geographic service area or population on a regular scheduled basis. There were approximately 6,500 sites as of 2007. The site must be operated as a part of the health center's current approved scope of practice (Bureau of Primary Health Care 2007). To be included in the study, the FQHC had to be located in the United States, have one site of delivery that was a community-based primary clinic, be rated as providing reliable data by the collecting agency, and report data in all 3 years of the study period. A total of 644 FQHCs were included in the final analysis with 1,932 health center years of data.

Study Design

The study employs a retrospective cohort design with multiple observations (Maxim 1999). The strength of this design is that the effect can be analyzed through multiple time periods. Visually, it can be depicted as X O_1 X O_2 X O_3.

Each O represents a different year of observation at the same health center. Thus, O_1 represents health center O in year 2005, O_2 is health center O in 2006, and O_3 is health center O in 2007. The Xs represent the presence of the variable of interest. In the case of this study, this variable is a continuous variable for the percentage of grant revenues as a percentage of the total revenues at the health center. Although the analyses cannot be used to make causal inferences, they will be able to show the impact of the variable of interest over time.

Data Sources

The Uniform Data System (UDS) is a core set of information appropriate for reviewing the operation and performance of health centers (Health Resources and Services Administration 2010). The UDS is a reporting requirement for grantees of the following HRSA primary care programs, as defined in the Public Health Services (PHS) Act: Community Health Centers, Section 330 (e); Migrant Health Centers, Section 330 (g); Health Care for the Homeless, Section 330 (h); and Public Housing Primary Care, Section 330 (i) (Health Resources and Services Administration 2010). The UDS is an annual census of aggregate-level health center data for all FQHSs. This study uses the UDS data provided by the Bureau of Primary Health Care (BPHC) for the years 2005, 2006, and 2007. The measures of interest are FTEs for physicians, nurse practitioners, physician's assistants, and all other staff. The cost measures are the medical, other clinical, enabling, and overhead costs.[1] The data also include the number of encounters by provider type, revenues by payer, patient attributes, and quality measures.

In addition, the Area Resource File (ARF) and Medicaid Statistical Information System (MSIS) were used to merge county- and state-level data with the UDS dataset based on zip code. The measures of interest from the MSIS and ARF are Medicaid spending per beneficiary, median household income in the county, and the number of hospital beds in the county. The National Ambulatory Medical Care Survey and National Center for Health Statistics Health Care Utilization data were used to generate expected health care utilization by age group. All prices were adjusted to constant 2007 dollars using the Medicare Economic Index and regionally adjusted using the Occupational Employment and Wage Statistics data from the Bureau of Labor Statistics.

Covariates

In the analysis we included actual versus expected variables to control for patient makeup as it relates to diabetes, hypertension, and utilization. We also included an urban–rural binary variable, race/ethnicity/age characteristics, Medicaid managed care funding as a percentage of total revenue, the ratio of nurse practitioners and physician's assistants to physicians, the total FTEs at the health center, and insurance status of the patients. Quality was measured by looking at the percentage of mothers who had prenatal visits in the first trimester (Shi et al. 2012).

Analysis

The analysis of technical efficiency is performed in multiple steps. In the first step, technical efficiency is measured using DEA models of multiple inputs and outputs, which are discussed later (Caves, Christensen, and Diewert 1982; Färe and Grosskopf 1992; Banker, Chang, and Natarajan 2005). The DEA scores were then used as the dependent variables in second-stage analyses to understand the determinants of technical efficiency (Hollingsworth 2003). The second-stage model includes the variables of interest and covariates which were drawn from relevant literature and theory that posit independent impacts on the technical efficiency of FQHCs. For this stage we estimate a two-part fractional response model with the DEA score as dependent variable (Baum 2008; J. Ramalho and da Silva 2009; E. A. Ramalho, Ramalho, and Henriques 2010; E. A. Ramalho, Ramalho, and Murteira 2011; Stavrunova and Yerokhin 2012).

The first part of the second stage models the conditional probability (as a function of covariates) that an FQHC is on the efficiency frontier. In our sample, approximately 20 percent of FQHCs were on the frontier. We estimated an instrumental variable (IV) probit model to identify the factors that primarily determine whether a health center is on the frontier or not. Instrumental variables were used to account for the potential endogeneity of grant funding. In the second part we investigated the drivers of efficiency for those FQHCs that are *not* on the efficiency frontier. This was done using a fractional response model, which was estimated using a two-step instrumental variables estimator (Papke and Wooldridge 2008). This estimator uses the residuals from a linear regression of the endogenous variable on the instruments (and other exogenous variables) as a covariate in a generalized linear model (GLM) for the fractional response (DEA score). We used 500 bootstrap iterations to calculate standard errors.

Returns to Scale

This study used Banker, Charnes, and Cooper's DEA estimator, which allows for variable returns to scale (VRS) (Banker, Charnes, and Cooper 1984). Constant returns to scale models were estimated, but the results were not significantly different from the VRS models. Three different DEA models were examined and the frontier was developed for each year; Figure 1 details the inputs and outputs that were modeled. To identify the various inputs and outputs used in similar DEA analysis studies, a literature search was performed. After examining the relevant literature, it was clear that three classes of inputs were used across all the studies; these were labor, costs, and capital. The outputs were generally some measure of patient volume and this was often differentiated by the provider who delivered the service. Output variables are almost always measures of physical activity such as patient days or discharges (Amico 2012). These variables are not case mix adjusted because data on patient diagnoses were not available.

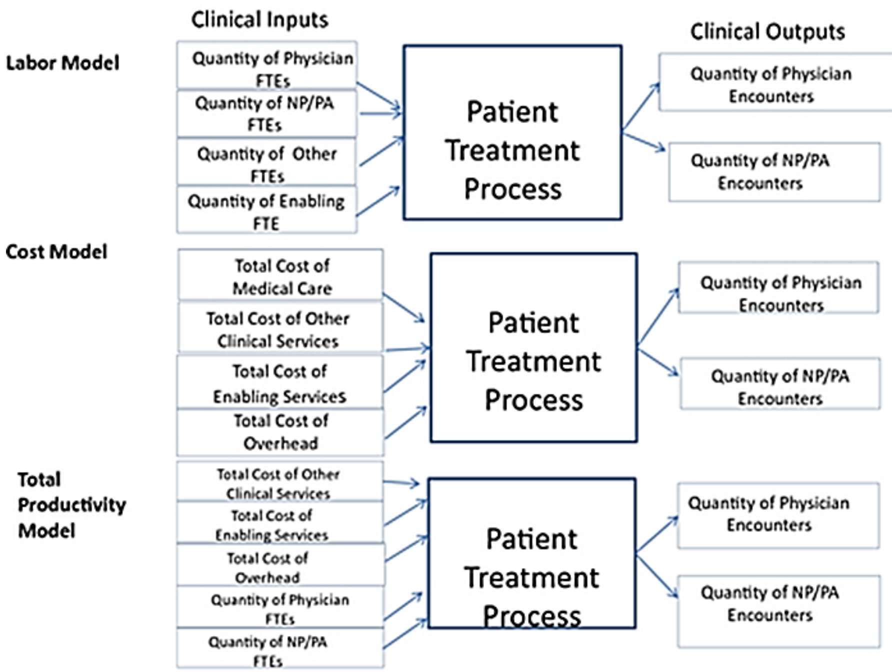

Figure 1. DEA Models, Inputs, and Outputs

Instrumental Variables

Grant funding is a potentially endogenous variable; we, therefore, employed instrumental variables to address this concern. For an instrumental variable to be valid (i.e., eliminate endogeneity bias), it may affect the dependent variable *only indirectly* through its effect on the endogenous explanatory variable. FQHCs must provide services to an underserved population or area as a requirement of receiving federal grant funding. The poorest states have the highest dependence on federal grants, which leads to the expectation that this percentage will vary by region based on income levels. The number of hospital beds in a county and the Medicaid spending per beneficiary are most likely not related to health center efficiency, but their regional variation is strongly related to grant funding, which is tied to serving underserved populations. Thus, these variables are strong candidates to be used as instruments to parse out the endogeneity of grant funding as an explanatory variable.

Research Question

Health centers dependence on grant revenue ranges from 1.5 to 100 percent with a median of 44 percent, mean of 46 percent, and a standard deviation of 22 percent. These grants represent a significant portion of health center revenues and the limited evidence posits that an increase in grant revenue will lead to a decrease in efficiency. Therefore, DEA efficiency is regressed on the continuous variable of grant revenue (and other covariates) to test the hypothesis that an increase in dependence on grant revenue will negatively affect efficiency. The hypothesis was tested for significance at the $\alpha = .05$ level and was conducted using STATA 11.2 (StataCorp 2009, College Station, TX).

Results

DEA Model

The average level of technical efficiency for the three models ranged between 65 percent efficiency and 75 percent efficiency from 2005 to 2007. However, there was a wide range of efficiency scores ranging from 28 to 100 percent in the labor model (1), from 10 to 100 percent in the cost model (2), and from 23 to 100 percent in the total productivity model (3). In 2005, 20, 14, and 21 percent of the observations were on the frontier for Models 1, 2, and 3, respectively. This decreased to 17, 13, and 18 percent in 2006 and 15, 13, and 18 percent in 2007. Table 2 gives a profile of high- and low-performing health centers using key environmental and health center descriptive statistics. There are significant differences between the high- (100 percent efficient) and low-performing health centers (<50 percent efficient) in grant percentage, actual versus expected utilization, diabetes and hypertension patients, patient age, insurance status, urban location, median household income, Medicaid spending per capita, operating margins, encounters, encounter costs, and the cost of medical staff. Low-performing health centers were more likely to be in urban settings, have lower operating margins, lower utilization, more reliance on grant funding, higher encounter costs, fewer overall encounters, lower medical staff cost, fewer children aged 0–5 years and adults over age 65 years, and more uninsured patients. On the other hand, these health centers were located in counties with significantly higher median incomes and higher Medicaid payments per capita. There was no significant different in the staff size, number of sites, FTEs per site, MMC percentage, women who had visits in their first trimester, Medicaid percentage, or the percentage of patients who do not speak English as a first language.

Table 2. High- and Low-Performing Health Centers and Their Characteristics

	Model 1		**Model 2**		**Model 3**	
	$\Theta = 100\%$	**$\Theta \leq 50\%$**	**$\Theta = 100\%$**	**$\Theta \leq 50\%$**	**$\Theta = 100\%$**	**$\Theta \leq 50\%$**
Obs.	333	157	260	487	344	145
Scale						
Total staff	103.96	83.39	92.03	85.81	105.11	81.72
No. of sites	6.15	7.20	5.94	5.52	6.03	7.15

FTE per site	19.69*	21.44*	15.74***	25.03***	18.57	21.17
Resource dependence						
MMC pct. (%)	0.10	0.12	0.08	0.09	0.10	0.12
Grant pct. (%)	.46***	.56***	0.48	0.51	.47***	.56***
Staff mix						
NP–PA pct (%)	0.38	0.40	0.42	0.43	0.38	0.40
Controls						
Actual versus exp utilization pct. (%)	.84**	.78**	.84***	.77***	.85***	.75***
Diabetes pct. (%)	0.05**	0.04**	.06**	.05**	.05***	.04***
Hyp. pct. (%)	.07***	.05***	.08***	.06***	.07***	.05***
Pct. 0–5 (%)	.12***	.10***	.10	.10	.12***	.10***
Pct. 65 + (%)	.10***	.06***	.09***	.08***	.09***	.06***
Black pct. (%)	0.12	0.12	0.12	0.11	0.12	0.12
Non-Eng. pct. (%)	0.18	0.22	.14**	.19**	0.17	0.2
Medicaid pct. (%)	0.29	0.27	0.26	0.27	0.28	0.28
Uninsured pct. (%)	.38***	.43***	.39***	.43***	0.39	0.43
Urban pct. (%)	.36***	.68***	.33***	.49***	.37***	.68***
Median House Inc. (000)	41.72***	49.4***	41.91***	44.27***	42.27***	49.07***
Medicaid per cap.	938.54***	1,046.63***	925.29	945.78	941.59*	1,012.99*
Quality						
First trimester pct. (%)	0.67	0.68	0.71*	0.67*	0.68	0.68
Other						

Operating margin	.05***	−.07***	.08***	−.05***	.06***	−.08***
Encounter cost	132.27***	165.91***	131.45***	157.75***	132.67***	170.54***
Total encounters (000)	54.59***	19.53***	51.92***	25.01***	53.07***	18.84***
FTE cost— medical (000)	182.58***	153.48***	178.31***	168.89***	179.86***	160.59***

Note. Mann–Whitney/*t*-test ****p* < .001, ***p* < .01, **p* < .05, DEA Models 1, 2, and 3, years 2005–2007. High performing = 100% efficient; low performing = below or equal to 50% efficient.

Probability of Being a Frontier Health Center

Table 3 shows the results for the probit estimation using IVs. This estimates the probability of a health center being on the frontier (e.g., being fully efficient). Holding all other factors constant, the percentage of grant revenue of total revenues did not impact the probability of a health center being on the frontier in any of the DEA models. While these were negative coefficients, they were not significantly different from zero.

Table 3. Probability of Being on Frontier: Generalized Estimating Equation with Instrumental Variables

	DEA 1	**DEA 2**	**DEA 3**
Total grant revenue (%)	−0.941	−3.012	−1.987
Medicaid managed care revenue (%)	−0.030	−1.023	−0.301
Ratio NP+PA/physician	−0.551	0.007	−0.437
Ln staff hours	−0.459*	−0.615**	−0.550***
Actual versus expected utilization	0.376	0.390	0.498
Actual versus expected diabetes	−0.155	−0.102	−0.104
Actual versus expected hypertension	0.035	0.188	−0.052
Patients 1–5 years old (%)	2.637	−0.735	1.003
Patients 65 and older (%)	0.610	−1.469	−0.236
Black (%)	−0.375	−0.035	−0.116

Non-English (%)	0.234	0.137	0.229
Medicaid (%)	0.144	−0.059	0.010
Uninsured (%)	0.224	0.806	0.678
Urban	−0.059	−0.003	−0.032
Ln county household income	−0.553*	−0.101	−0.339
Constant	10.478**	8.332*	9.709***

****p* < .001, ***p* < .01, **p* < .05.

Health centers that had more staff hours, holding all else constant, were less likely to be on the frontier in all three models. The percentage of MMC revenue had a consistently negative coefficient, although it was not statistically significant in any of the models.

Nonfrontier Health Centers

For the health centers that were not on the frontier, we estimated a two-part fractional response model with instrumental variables (Papke and Wooldridge 2008). We used the number of hospital beds in the county and Medicaid spending per beneficiary as instruments for grant revenues as a percentage of total revenues. The first-stage regression gives an F-statistic of 5.95, 6.65, and 7.03 for the three DEA models, respectively. This is evidence that the two IVs are correlated with the dependent variable, which is a necessary condition for an IV. The residuals from this linear regression were included in a GLM model with a probit link and standard errors clustered at the health center level. Table 4 shows the results for the nonfrontier health centers.

Table 4. Nonfrontier Centers: Generalized Linear Model with Instrumental Variables

	DEA 1	**DEA 2**	**DEA 3**
Total grant revenue (%)	−1.368*	−0.055	−1.414*
Medicaid managed care revenue (%)	−0.223*	0.090	−0.158
Ratio NP+PA/physician	−0.007	−0.217*	−0.030
Ln staff hours	0.042*	−0.010	0.038
Actual versus expected utilization	0.158	0.305**	0.166
Actual versus expected diabetes	−0.015	−0.024	−0.004
Actual versus expected hypertension	0.134	0.179*	0.145

Patients 1–5 years old (%)	0.636	1.221*	0.668
Patients 65 and older (%)	0.09	0.190	0.002
Black (%)	−0.019	0.044	−0.005
Non-English (%)	−0.057	0.170	−0.045
Medicaid (%)	−0.386*	−0.347	−0.590**
Uninsured (%)	0.628*	−0.123	0.59
Urban	−0.01	−0.025	−0.007
Ln county household income	−0.225***	−0.078	−0.174**
Residuals from IV regression	0.943	−0.182	1.050
Constant	2.629***	−0.700	2.222***

****p* < .001, ***p* < .01, **p* < .05.

The nonfrontier health centers showed a negative relationship between grant revenues and efficiency in two of the three DEA models. This is likely due to the fact that increased grant revenues distort competitive pressure on the health centers and thus allow for increased levels of inefficiency.

MMC as a percent of total revenues has mixed signs and is not significant in any of the models. The percentage of NPs and PAs is mixed across the models and years. The sign does not change between models, but it is not consistently significant across all three models. It has a negative and significant coefficient in Model 2, which indicates that it negatively affects efficiency. Model 2 is the efficiency score that has cost inputs, so a health center with fewer physicians will be less technically efficient when cost is the input variable. Finally, the log of staff hours was consistently positive in all models and significant in Model 1. The number of FTEs per site was also tested and had the same sign of the coefficient while the number of delivery sites was not significant. This provides evidence that larger health centers may have increased technical efficiency. This in contrast to the finding that increased staff hours negatively increased the probability of being on the frontier.

Discussion

With the passage of the ACA in March 2010, policy makers, funders, and health providers are searching for ways to improve health system performance. There is an increasing role for FQHCs, as they have been identified as key players in this effort. An additional U.S.$ 11 billion has been dedicated to FQHCs over the next 5 years in expectation that FQHC capacity will expand to 40 million patients by 2015 (Arvantes 2010). This expansion includes the estimated 32 million additional people who will enter the health system by 2014, creating an even greater demand for primary care services than what currently exists (Arvantes 2010). Improvements in efficiency will buy more health care for populations that are in need. This will enable FQHCs to step into a greater role as is outlined in the ACA.

FQHCs are critical providers of primary care to vulnerable populations across the United States and will continue to grow in significance with the impending expansion of Medicaid in 2014. Understanding the factors that determine FQHC's efficiency is critical to craft evidence-based policies that support increased technical efficiency of the FQHC program. In doing this, the poorest of our population will have a much more accessible safety net system where they can receive quality health care. In addition, the entire health system will benefit in the long term from the reduction in overall health expenditures and unnecessary utilization of health care (Ku, Richard, and Dor 2009; Rothkopf et al. 2011). The current research found that anywhere from 39 to 45 million patient encounters could have been delivered instead of the actual total of 29 million in 2007. In addition, the two dominant findings of this research were that an increasing reliance on grant revenues leads to decreased technical efficiency in health centers that are not fully efficient and that larger health centers negatively increase the probability of being fully efficient, but increase the probability of being efficient, given that one is not fully efficient.

FQHC's heavy reliance on grant funding was associated with decreased technical efficiency in FQHCs. X-inefficiency theory explains that this is due to distortion of market competition that occurs with grant revenues. Grant revenues do not force health centers to have an efficient business model, but rather to compete for more grant funding. Nonprofit organizations that rely heavily on grant funding may not maximize their outputs due to the lack of market pressure. It is a requirement that these health centers have quality improvement plans in place to receive Section 330 funding from the federal government, but there are no performance requirements. Thus, it may be possible that health centers with higher revenue from grants are not operating as efficiently as they could.

With the expansion of Medicaid in 2014, health centers should begin preparing for a new business model that will be less reliant on grant revenues and more reliant on patient revenues. This is because current grant funding is intended to cover the uninsured patients and they will begin to decrease in 2014 with the expansion of universal coverage. Overall, the percentage of funding at health centers comprising grant revenues is decreasing, and Medicaid will likely become the most dominant payer in upcoming years; it is unlikely that half of FQHC revenues will continue to come from grants as is the case currently.

Larger health centers, as measured by total FTE, were associated with increased levels of technical efficiency for nonfrontier health centers. However, the increased staff size negatively decreases the probability of being a fully efficient health center. Therefore, health centers with large staff sizes are not likely to be fully efficient, but the nonfrontier health centers are likely understaffed. The implications of these mixed findings are not clear as we expected economies of scale to be found. When we looked descriptively at administrative hours as a percentage of the total, they decreased as the health centers got bigger. The diseconomies of scale may be due to more complex systems, sorting through more no shows, and difficulty in coordinating patient care. However, more research is needed to understand qualitatively why FQHCs experience diseconomies of scale as they get larger.

Future Research

It is important to further understand the determinants of cost efficiency in FQHCs. Technology and cost efficiency are highly correlated, but they do not provide a one-to-one correlation. While the current research may provide some clues about cost efficiency, future research is still needed. This is outside of the scope of this study, but policy makers and managers could benefit greatly from an increased evidence base on what makes FQHCs cost efficient. Along with this, it is critical to expand the knowledge base surrounding quality in FQHCs. Currently, there are a small number of process measures, but in the coming years the UDS is continually rolling out more extensive quality measures. Any future research must consider the impact of quality in concert with efficiency.

One of the shortcomings of the available data is that the health centers report the data from all their satellite sites as one aggregate health center, thus making it difficult to fully understand the impact of scale. It would be useful to have each satellite report its own data, as many of these health centers are autonomous primary care clinics that all operate under the umbrella of one health center.

One final area that should be explored further is the possibility of providing benchmarks for health centers by studying the most efficient health centers. To provide fair comparisons, health centers can be separated based on their location, size, and case mix. In doing this, six separate categories of health centers will be created and the frontier health centers can be examined to provide best practice benchmarks. These benchmarks can provide very useful information to health centers that are seeking to improve their efficiency by measuring their performance as well as their overall makeup in comparison to similar health centers that are more efficient.

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Note

1. Costs are calculated on a cash basis, whereas revenues are computed on accrual.

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