MEASURING EFFICIENCY OF FEDERALLY QUALIFIED HEALTH CENTERS: A MULTI MODEL APPROACH USING DATA ENVELOPMENT ANALYSIS (DEA) & LATENT CLASS ANALYSIS (LCA)

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"MEASURING EFFICIENCY OF FEDERALLY QUALIFIED HEALTH CENTERS: A MULTI MODEL APPROACH USING DATA ENVELOPMENT ANALYSIS (DEA) & LATENT CLASS ANALYSIS (LCA)"

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Abstract

There are 1300 federally qualified health centers (FQHCs) in the United States providing the health care to underserved and uninsured population. These FQHCs serve the patients irrespective of their ability to pay. Using the resources effectively, these FQHCs can provide better health care. In this study of prenatal care, we measure the efficiencies of the FQHCs using data envelopment analysis (DEA). As in service industry, where quality is of at most importance, we used two different DEA approaches considering quality called the Two model DEA approach by (Shimshak, D., & Lenard, M.L.,2007) and Quality adjusted DEA approach by (Sherman, H.D., & Zhu, J, 2006). Efficient frontiers are determined by using these DEA approaches. There are differences that exists across FQHCs due to various factors to include demographic characteristics of patients visited the FQHCs, operational characteristics of health centers. Latent class analysis is performed before performing the DEA to classify the FQHCs into different classes based on the regional and population measures. Four different models namely aggregated Shimshak & Lenard and aggregated Sherman & Zhu models (DEA model is run on the whole sample), partitioned S&L and partitioned S&Z models (DEA model is run individually by class) have been used to determine the efficiencies of the FQHCs. Using the S&L approach, it is found that the FQHCs that formed the efficient frontier is of smaller FQHCs whereas the S&Z approach has a mix of small and large FQHCs. Based on the results determined, more insights are provided on the FQHCs and the models used in the analysis.

Chapter 1: Introduction

Federally qualified health centers (FQHCs) have been providing health care services to underserved and uninsured patients since 1960s. FQHCs are local, nonprofit and community owned clinics. In early 1960s, many inner cities & rural areas had significant challenges to include poverty and adequate access of health care. To improve the health outcomes, the FQHC model was initiated for the local population. After the passage of the Economic Opportunity Act in 1964, two FQHCs has been started as a demonstration project in Massachusetts & Mississippi. FQHCs provide health services like access to primary and preventive care to disadvantaged population thus helping to reduce health disparities. Although there are significant challenges regarding access and disparities, the FQHCs provided much needed access and reduced the disparities with minority population (Kantayya & Lidvall, 2010). Studies have found that there is a huge improvement in FQHCs providing access to prenatal care and reduction in low birth weights (Kantayya & Lidvall, 2010). Currently, there are nearly 1300 FQHCs in the United States serving the under-served and uninsured patients. All FQHCs are required to provide the service regardless of the ability to pay. FQHCs serve 1 in 5 low income children. Approximately 70% of the patients have family incomes at or below poverty level, where as 40% of the patients are uninsured & another 36% depend on Medicaid. Though these FQHCs are federally funded, most of the funding comes from grants & donations. In order for a health center to be qualified as an FQHC and to receive federal funding, there are certain requirements to meet.

1. It is required that board consists of patient majority. The board members serve as a community representatives and make decision on the services that are provided.
2. FQHC location in a federally designated medically underserved area

3. A nonprofit, public or tax exempt status
4. Provision of comprehensive health care services and other enabling services such as translation, transportation
5. Provision of health care services regardless of the patient's ability to pay.

Using the resources efficiently, FQHCs can provide health care services to more patients and provide better quality outcomes. Our research is focused to evaluate the efficiencies of FQHCs. Evaluating efficiencies of the FQHCs will help to identify the high performing FQHCs whose practices might be adopted by other FQHCs to be more efficient. Our study examines the quality of prenatal care and birth outcomes of patients served at FQHCs in 2015 in evaluating the FQHC efficiencies. Data envelopment analysis (DEA) model is developed to evaluate the efficiencies of these FQHCs. DEA uses frontier approach to determine the efficient FQHCs.

Data envelopment analysis (DEA) originally developed by Charnes, Cooper and Rhodes is a mathematical model developed to evaluate the efficiency of different decision making units (DMUs). DEA model compares the set of inputs consumed & outputs produced to evaluate the efficiency. DEA model evaluates the decision making units by comparing the efficiencies of any decision making unit to the efficiencies of other decision making units used in the model (Charnes, Cooper & Rhodes, 1981). When evaluating the efficiency of any DMUs in the service industry, operational efficiency isn't the only measure that is a deciding factor in finding the efficient units. When operational efficiency is the only measure to evaluate the DMUs, DMUs with higher operational efficiency but low quality efficiency may form the efficient frontier. Therefore, quality measures should be taken into account when evaluating the efficiencies of DMUs in service industry.

In our research, we use a multi-stage, multi-model approach called, a two model DEA approach developed by (Shimshak, D., & Lenard, M.L., 2007) and quality adjusted DEA developed by (Sherman, H.D., & Zhu, J.,2006) to measure efficiencies of the FQHCs. By incorporating quality in the DEA model, FQHCs with high operational efficiency and acceptable quality efficiency are deemed as the efficient FQHC. The quality measures used in the model are the percentage of the prenatal patients who received prenatal care in the first trimester and the percentage of low birth weight births.

There are differences that exist across FQHCs due to various factors to include demographic characteristics of patients visited the FQHCs and operational characteristics of health centers. Studies show that there is an association between FQHCs operational efficiency & contextual factors like percentage distributions of Medicare, Medicaid and racial ethnicities. Factors like poverty, minimal education, and inadequate access to medical care in rural areas are more prevalent than the urban areas. Approximately 40% of the rural families in the United States do not have health insurance. Studies on rurality and birth outcomes show that, the other 60% though they have government subsidized health insurance plan failed to have a consistent prenatal plan with health centers which resulted in poor or worse birth outcomes compared to the patients without such insurance (Bushy A., 1998).

Given the differences, DEA performed with all the FQHCs in one single model might result in the biased evaluation of these FQHCs. To overcome this biased evaluation, a latent class analysis (LCA) is performed based on the sociodemographic characteristics of the patient population in FQHCs and their region settings which identifies the unobserved subgroups within the population of FQHCs. Individual subgroup classes of FQHCs are identified based on the sociodemographic characteristics.

In this research, we examine four different approaches in evaluating the efficiencies of the FQHCs.

1. Single DEA models with all FQHCs called Aggregated Shimshak & Lenard (S/L) & Aggregated Sherman & Zhu (S/Z) approach
2. DEA models on individual subgroup classes identified using LCA called Partitioned S/L & Partitioned S/Z approach.

In this research, we provide insights on the efficient FQHCs by the efficient frontiers determined using both the models mentioned above.

Chapter 2: Literature Review

2.1 Data Envelopment Analysis (DEA)

Charnes, Cooper & Rhodes used DEA in 1978 to evaluate public schools in the United States. This is the first time DEA has been ever used to evaluate efficiency. Efficiency is measured as the ratio of weighted sum of outputs to the weighted sum of inputs. Charnes later in 1978 converted this fractional programming model to a linear programming model. Later in the years, many extensions to this DEA has been developed by other researchers. (Banker, Charnes & Cooper, 1984) developed a variable returns to scale model, an extension to the DEA model developed by Charnes, Cooper, Rhodes. There are various extensions to this DEA model to include, a two model DEA approach developed by (Shimshak, D., & Lenard, M.L., 2007) and quality adjusted DEA developed by (Sherman, H.D., & Zhu, J, 2006) to measure efficiencies. In our research we use the above mentioned two model DEA and quality adjusted DEA in measuring the efficiencies of federally qualified health centers with focus on prenatal care.

Data Envelopment Analysis (DEA) has been widely used to benchmark the performance in service industries like education, banking, health industry etc., where there is no well-defined standard for efficiency. Benchmarking allows to compare the individual units in the performance analysis with respect to their peers where there are multiple measures of performance. DEA uses the set of inputs and outputs and provide the efficiency of the units considered in the analysis. In service industry, we have various measures which can be used as inputs and outputs in determining the efficiency. But we need to be cautious in determining what measures we can use as inputs and as outputs. Depending on the purpose of the analysis, inputs considered in one method of analysis can be considered as outputs in another method of analysis. So, it is imperative to clearly define the purpose of analysis before choosing the inputs and outputs for the analysis.

There are many literature papers that provide the insights on how DEA has been used. A study published by (Wade D. Cook, Karou Tone, Joe Zhu, 2013) tells us that the purpose of the performance measurement influences to develop the DEA model for the research. The paper further suggests that, before developing a DEA model, there are a few critical questions to answer to include the purpose of the analysis, the inputs & outputs chosen, the orientation of the model. It is imperative to have a clear understanding of the process being evaluated which in turn drives the choice in choosing inputs and outputs that can be considered in evaluating the process. Studies from (Banker, R.D., Charnes, A., Cooper, W.W., Swarts, J., and Thomas, D.,1989) suggests that number of DMUs should be twice the number of inputs and outputs combined. Unlike regression analysis where sample size is critical, DEA when used as benchmarking tool, the sample isn't critical as the tool focuses on the individual DMU performance.

2.2 DEA in health care

There are numerous research papers that have been published using DEA as a performance measure in health care industry. (Gullipalli, 2011) used DEA to determine the efficiency of 41 member clinics of Kansas Association of Medically Underserved (KAMU). In evaluating the physician's performance, (Chilingerian, J.A and Sherman, H.D, 1996) identified the best practice primary care physicians using DEA. (Huang, Y-G and McLaughlin, C.P., 1989) performed DEA to evaluate the rural primary health care programs. Though there are many papers published on DEA in health care, there aren't many papers that considered quality to be an indicator of the performance. Unlike other industries, service industries especially in health care industry, quality should be given importance in determining the efficiencies of health centers.

A case study conducted by (Jose Manuel, Cordero Ferrera, Eva Crespo Cebada, 2013) demonstrates the importance of quality and the socio-demographic characteristics of the patients served by the health center in determining the efficiencies of the health center using a four-stage procedure. To measure the economic efficiency in primary health care, quality of care and socio-demographic characteristics of the patients has been considered to overcome the biased analysis of determining the efficiency of health centers by just considering the quantity outputs. Population density and the elderly ratio has been identified as the factors in their study that influences the performance of the health centers. With the inclusion of quality and socio-demographic characteristics in the analysis, the efficient frontier is determined to be used as a reference set for the inefficient units. The study showed that, the health centers operating in the bigger cities have been affected negatively with the inclusion of socio-demographic characteristics like population density and elderly ratio which therefore is believed that inclusion of socio-demographic characteristics of patients is important to determine the efficiency frontier. A study from (Shriram Marathe et al, 2007) shows that, the there is an association between the efficiencies of Community Health Centers (CHCs) and the contextual factors like percentage of patients with Medicare, Medicaid, Hispanic population in the area and organizational factors like staffing and federal funding. (J. Salinas- Jimenez, P. Smith, 1996) explored the role of quality indicators in primary care and provided insights on 90 Family Health Service Authorities (FHSA) using DEA with the inclusion of quality indicators. Seven important quality indicators have been used in the analysis to include a few like general medical practitioners, percentage of practices employing a practice nurse, the percentage of general medical practitioners with a patient list of less than 2500 patients etc.,

In our research, insights have been developed on the FQHCs by comparing the efficiency frontiers determined by both models (two-model DEA & quality adjusted DEA).

Chapter 3: Data Collection & Choosing the Model

3.1 Data Source

Under the health center grant program, Health Resources and Services Administration (HRSA) administered by the Bureau of Primary Health Care (BPHC), all grantees are required to report information on patient demographics, services provided, clinical indicators, utilization rates, costs and revenues every year. Data for this study came from multiple sources to include Uniform Data System (UDS) maintained by the Bureau of Primary Health Care (BPHC), US Census American Community Survey (ACS; 2010-2014).

2015 FQHC level data come from Uniform Data System (UDS). UDS is an integrated reporting system used by all grantees funded for community health center, migrant and seasonal farmworker, health Care for the homeless, and public housing primary care. The UDS collects FQHC level information on services, patient characteristics, clinical indicators, age & race/ethnicity, cost and revenues, Staff. It also collects information at regional zip code tabulation area (ZCTA) level. Regional zip code tabulation area (ZCTA) - level data is collected from the US Census American Community Survey

3.2 Choosing variables of interest (inputs & outputs)

Variables related to pregnancy services and pregnancy outcomes (annual number of prenatal patients served, prenatal patients who delivered, prenatal patients who had access to prenatal care, low birth weight) has been considered as the outputs. Out of the output variables chosen, we consider annual number of prenatal patients served and prenatal patients who delivered as operational outputs. Percentage of prenatal patients who had access to prenatal care and percentage of low birth weights are considered as the quality outputs.

Prenatal care refers to the primary care provided to the pregnant woman prior to birth. This provides regular check-ups that allow providers to keep the mother and the baby healthy during pregnancy. Access to prenatal care helps in better birth outcomes. Birth weight is most likely to benefit from access to the prenatal care. Therefore, output variables considered (annual number of prenatal patients, prenatal patients who delivered, percentage of prenatal patients with access to prenatal care and percentage of low birth weight) fits to our study in evaluating pregnancy outcomes of the FQHCs.

We considered twelve variables health center service grant expenditures, other non-patient revenue, total cost, FTE staffing (Medical, Primary Care Physician, Non-Primary Care Physician, Nurse Practitioner/ Physician Assistant/ Certified Nurse Midwife, Dental, Mental Health, Substance Abuse, Vision, Enabling) as the inputs in the DEA model.

2015 data on the inputs and outputs is collected from UDS. Data for 1375 FQHCs is collected. Out of the 1375 FQHCs, there are 190 FQHCs that served five or fewer prenatal patients and 30 FQHCs that had zero Medical FTEs. These 220 FQHCs are excluded from the DEA analysis. Further, FQHCs outside of the 50 US states and FQHCs that served less than 100 total patients has been excluded from the DEA analysis, leaving a sample of 1,111 FQHCs to be included in the DEA analysis.

Mean Values		Total (n=1,111)
DEA outputs	Prenatal Patients	483
	Prenatal Patients who Delivered	255
	Access to Prenatal Care (First Prenatal Visit in 1stTrimester)	76%
	Low Birth Weight Index	91.57%
DEA inputs	Health Center Service Grant Expenditures	2,872,311
	Other Non-patient Revenue	3,160,352
	Total Cost	16,931,055
	Medical FTE	56.79
	Primary Care Physician FTE	9.53
	Non-Primary Care Physician FTE	0.34
	NP/ PA/ CNM FTE	8.69
	Dental FTE	12.29
	Mental Health FTE	6.52
	Substance Abuse FTE	0.80
	Vision FTE	0.46
	Enabling FTE	15.61

Table 1. Mean values over the set of 1,111 FQHCs for DEA inputs & outputs

	class 1 (n=291)	class 2 (n=402)	class 3 (n=148)	class 4 (n=157)	class 5 (n=113)

DEA outputs	Prenatal Patients	217	769	342	639	119
	Prenatal Patients who Delivered	115	404	176	338	68
	Access to Prenatal Care (First Prenatal Visit in 1stTrimester)	79%	74%	68%	74%	89%
	Low Birth Weight Index	91.06%	91.37%	92.50%	92.15%	91.59%
DEA inputs	Health Center Service Grant Expenditures	2,435,900	3,277,457	3,146,671	3,103,371	1,874,487
	Other Non-patient Revenue	1,474,048	4,666,532	2,659,286	4,424,820	1,044,125
	Total Cost	11,035,757	23,806,522	10,234,022	21,646,478	9,872,946
	Medical FTE	39.93	76.70	37.12	68.86	38.43
	Primary Care Physician FTE	5.96	13.15	5.81	12.73	6.32

	Non-Primary Care Physician FTE	0.14	0.27	0.10	1.27	0.09
	NP/ PA/ CNM FTE	7.38	10.91	6.07	8.92	7.25
	Dental FTE	8.80	18.53	7.56	12.33	5.15
	Mental Health FTE	4.34	9.83	3.15	7.85	2.89
	Substance Abuse FTE	0.27	1.53	0.50	0.69	0.14
	Vision FTE	0.14	0.75	0.20	0.77	0.12
	Enabling FTE	8.89	22.50	13.07	20.24	5.31

Table 2. Mean values over the set of FQHCs for DEA inputs & outputs by class

3.3 Orientation of the model

The orientation of the model has to be chosen based on the purpose of our analysis. We have two different orientations.

3.3.1 Input-Oriented Model

In this model, the inefficient units are made efficient through the proportional changes in inputs while the proportions of output are kept constant.

3.3.2 Output-Oriented Model

An inefficient unit is made efficient by increasing the proportions of the output keeping the proportions of inputs unchanged.

Input variables chosen for our model (health center service grant expenditures, other non-patient revenue, total cost, FTE staffing) are under the control of the FQHCs rather than the outputs. Therefore, input-oriented model is chosen.

3.3.3 Returns to Scale

The frontier determined by the basic DEA model developed by Charnes, Cooper and Rhodes exhibits constant return to scale (CRS) i.e., increase in inputs results in linear proportionate increase of outputs. In our study, constant returns to scale cannot be applied as we cannot observe linear proportionate increase in outputs with increase in inputs. For example, increasing the number of FTEs, cannot necessarily guarantee the linear proportional increase in the number of prenatal patients served at FQHCs.

Therefore, input-oriented, variable returns to scale (VRS) model is chosen for the DEA analysis.

Chapter 4: Latent Class Analysis

Latent class analysis is a clustering methodology that identifies the latent subgroups within populations based on observed indicators. LCA approach uses the maximum likelihood function to estimate the parameters with an iterative estimation approach (Collins & Lanza, 2010). One of the key things in the latent class analysis is the model selection and determining the optimal number of latent classes. For this model selection and to determine the optimal number of latent classes, several measures of model fit based on the simulation studies namely information criteria (the Bayesian Information Criteria (BIC), the Sample-Adjusted Bayesian Criteria (SABIC) and the Akaike Information Criteria (AIC) and likelihood-based tests (Lo-Mendell Rubin) are considered. Entropy, a measure of disambiguation between individual classes also aids in the model selection (Nyland KL, Asparouhov T, Muthén BO, 2007).

In our study we use twelve variables to describe the patient population as well as regional measures. Data on the FQHC patient demographics is collected from the 2015 UDS. Six measures on patient population to include patient age distribution, % of patients who are non-white, % of patients best served in another language, % of patients in poverty, patient insurance status (% if uinsured patients and the total number of patients served at the FQHC. Regional measures data come from US Census American Community Survey (ACS; 2010-2014) and Behavioral Risk Factor Surveillance Survey (BRFSS; 2009-2012). Information on the demographic context of FQHCs are collected using the following four measures, % of non-white population living in the FQHC service region, % living in poverty, insurance status of the regional population (% uninsured, % on Medicaid), % of service region population with no usual source of health care. Two additional measures of urbanity were included, population density of the service region (population per square mile) and a binary indicator of the U.S. Census designation of urban/rural status of the service region (0 "rural" 1 "urban"). Both the continuous measures of population density and total number of FQHC patients were transformed to adjust the skewness by taking their natural log.

Using the twelve measures of FQHC regional and patient population characteristics, a latent class analysis was performed and solutions between two and seven classes were estimated. Entropy was highest for the four class solution and declined slightly for the five and six class solution and a slight increase for the seven class solution. The three information criteria measures declined as a the class number increased and were lowest for the seven class solution implying that this solution was ideal based on these measures. The Lo-Mendell Rubin test was significant for two through five classes, indicating that the five class solution was optimal. Model comparisons indicated that the solution with five classes to be the best fit.

Number of Latent Classes	**Entropy**	**AIC**	**BIC**	**SABIC**	**Lo-Mendell Rubin Adjusted LRT test**	
					value	***p value***
2	0.883	-18442.5	-18193.2	-18345.7	3506.93	0
3	0.9	-19877.4	-19539.8	-19746.3	1456.97	0
4	0.903	-21276.3	-20850.4	-21110.9	1421.24	0
5	0.894	-22052.9	-21538.7	-21853.2	804.05	0.007
6	0.884	-22638.2	-22035.7	-22404.2	614.27	0.195
7	0.89	-23115.6	-22424.8	-22847.3	518.88	0.403

Table:3 Information on model fit for latent class solutions

Class 1 consist of FQHCs primarily in the rural areas (11% urban) with an average population density of 131 individuals per square mile. Class 2 is also comprised mostly with the FQHCs in the rural areas (7% urban) with an average population density of 192 individuals per square mile.

Class one patients are more likely to be children, non-white, living in poverty and either uninsured or Medicaid compared to the patients served in the class 2. Therefore, we label class 1 as *More Diverse, Rural Poor* (26% of the sample) Class 2 FQHCs were more likely to be older, white patients on Medicare. Therefore, we label class 2 as *Older-Rural Whites* (12% of the sample). Class 3 consists of FQHCs located primarily in urban areas with a low rate of poverty and a low rate of medically uninsured individuals. These FQHCs in class 3 serve an average of 26,000 patients annually, with a majority of the patients to be children compared to other classes. Therefore, we label class 3 as *Large Urban Serving Children* (33% of the sample). Class 4 consists of FQHCs primarily in densely populated areas with over 10,000 individuals per square mile on average with patients with high rates of poverty, racial minorities, medically uninsured individuals and individuals who lack access to a usual source of medical care. We label this class as *Dense Urban Poor Racial Minorities* (14% of the sample). The fifth and final class of FQHCs was characterized by its high percentage of patients who lacked medical insurance (61% uninsured). We label this class as *Uninsured Patients* (15% of the sample)

	Full Sample	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
		More Diverse, Rural Poor	*Older Rural Whites*	*Large Urban Serving Children*	*Dense Urban Poor Racial Minorities*	*Uninsured Patients*
Regional Characteristics						
Population Density (pop/sq. mile)	2,135	131	192	1,467	10,004	1,097
Proportion Urban	45%	11%	7%	69%	75%	54%
% non-white	0.279	0.184	0.158	0.288	0.516	0.293
% in poverty	0.177	0.175	0.174	0.154	0.236	0.178
% on Medicaid	0.249	0.233	0.243	0.230	0.360	0.217
% uninsured	0.123	0.124	0.111	0.098	0.159	0.154
% with no usual source of care	0.199	0.191	0.176	0.176	0.252	0.230
Patient Characteristics						
Total number of patients	17,926	13,117	10,982	25,910	20,681	11,943

% patients who are children	0.264	0.262	0.184	0.319	0.271	0.202
% patients who are elderly	0.089	0.107	0.209	0.060	0.057	0.058
% non-white patients	0.545	0.304	0.172	0.661	0.861	0.707
% of patients best served in another language	0.170	0.057	0.032	0.226	0.253	0.273
% of patients in poverty	0.669	0.601	0.472	0.718	0.777	0.734
% of uninsured patients	0.273	0.233	0.141	0.215	0.236	0.605
% of patients on Medicaid	0.432	0.361	0.270	0.578	0.595	0.210
% of patients on Medicare	0.101	0.126	0.234	0.073	0.062	0.053
N	1,331	350	156	432	191	202
Proportion	100%	26.3%	11.7%	32.5%	14.4%	15.2%

Table 4. FQHC patient and regional characteristics, means by latent class membership

Chapter 5: Methodology & Results

5.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a benchmarking technique originally developed by Charnes, Cooper and Rhodes. It is intended as a method for performance evaluation and benchmarking against best practice. It uses linear programming as a technique for the estimation of productive efficiency of decision making units (DMUs) that have multiple inputs and outputs. Unlike regression models, DEA builds an empirical production frontier without any functional form imposed on it. Efficiency is measured relative to the estimated production frontier.

5.2 Two model approach by Shimshak & Lenard

When we apply DEA to service industry, decision making units are found to be efficient with high operational output measures but have low output quality. Decision making units which are efficient based on high operational output measures and high quality should form the production frontier. In order to have quality measures in the analysis, we use two model approach to measure operational and quality efficiency with DEA.

5.2.1 Aggregated S&L approach

In this approach, we evaluate two models simultaneously, one measuring operational efficiency and the other measuring quality efficiency. FQHCs with acceptable high operational efficiency & acceptable high quality efficiency forms the efficient reference set.

DEA model for operational outputs is run over a set of all FQHCs and another DEA model for quality outputs is run over a set of all FQHCs. Operational & quality efficiencies are identified in this analysis. We refer to these efficiencies as OpEff_Initial & QuEff_Initial. FQHCs with an OpEff_Initial as one and unacceptable low QuEff_Initial is taken off from the further analysis to ensure the efficient reference set for operational outputs has FQHCs with acceptable quality efficiency. FQHCs taken off from the further analysis retains their operational efficiency as one. DEA models for both operational outputs & quality outputs are run again over a new set of FQHCs. This process continues until we get an efficient reference set for operational outputs with an acceptable quality efficiency. And also the process repeats for the quality outputs model until we get an efficient reference set for quality outputs with an acceptable operational efficiency. We refer to these efficiencies at the end of the iterative process as OpEff_Final & QuEff_Final.

Setting thresholds for quality outputs

From the 2017 HRSA Annual performance report, the target for the fiscal year 2015 for prenatal patient access during the first trimester was 66% which we will refer as Quality_Access and the target for low birth weight (<2500 grams) was 5% below national rate. The National Center for

Health Statistics reports that 8.07% of babies born in 2015 were born with low birth weight. So applying this HRSA target to the 2015 national rate gives a target for low birth weight rate which is 0.95*0.0807=7.67%. We will use one minus the low birth weight rate as our low birth weight index, as DEA requires that outputs be scaled so that larger values denote better performance. This is the rate of non-low birth weight births with a target value of 92.33%. We will refer to this measure as Quality_LBWI.

Examining the QuEff_Initial scores relative to the targets (Quality_Access= 66%, Quality_LBWI=92.33%) found that a threshold of 0.95 will work well to have an acceptable high average performance. When determining the efficient FQHCs, we consider FQHCs with the operational & quality efficiencies above these thresholds as efficient. We use the same 0.95 as the threshold for operational efficiency.

There were 435 FQHCs with an OpEff_Final of one and unacceptable low QuEff_Final that were removed from the analysis during the iterative process. Examining the results, 50 FQHCs were found to be operationally efficient with the quality efficiency above the threshold. Efficient FQHCs were from all the classes identified in the LCA analysis. 16 were of class 1, 4 were of class 2, 9 were of class 3, 16 were of class 4 & 5 were of class 5.

Looking into the operational outputs, the average number of prenatal patients served by these efficient FQHCs is 78 which is less than the average of the sample of FQHCs used in the analysis. Average of the prenatal patient deliveries is 42 which is again less than average of the prenatal patient deliveries of the total FQHCs used in the analysis. These efficient FQHCs have an average quality outputs of 78.69% for quality access and 94.01% for non-low birth weight births which is clearly more than the quality output targets of 66% & 92.33% for Quality_Access & Quality_LBWI respectively. These FQHCs that are found to be efficient from the analysis are smaller FQHCs with an average of 5068 total patients served annually which is less than the average of the total patients of the set of FQHCs used in the analysis. Class 4 had the highest average of the total annual patients among the efficient FQHCs followed by class 1 & class 4.

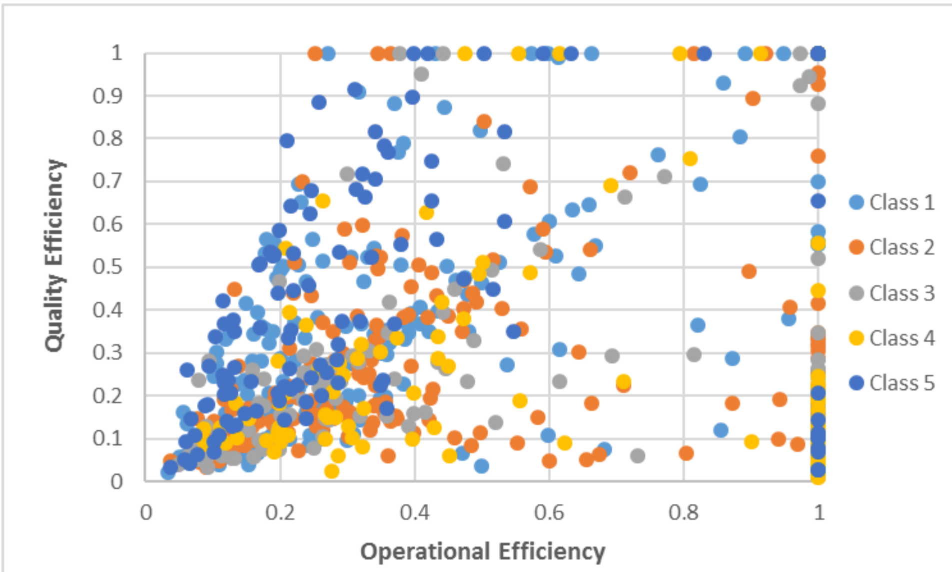

Figure 1. Operational Efficiency vs Quality Efficiency- Aggregated S&L method

The table below shows the descriptive summary statistics of final operational efficiencies by class

Class	Number of FQHCs	Operational Efficiency		Quality Efficiency	
		Mean	**Std. Deviation**	**Mean**	**Std. Deviation**
1	291	0.499	0.366	0.325	0.301
2	402	0.701	0.366	0.176	0.207
3	148	0.61	0.373	0.268	0.283
4	157	0.736	0.343	0.275	0.325
5	113	0.356	0.295	0.470	0.333
Total	**1111**	**0.606**	**0.377**	**0.2271**	**0.290**

Table 5. Operational Efficiency and quality efficiency by class- Aggregated S&L method

From the table 5, we can notice that class 4 has the highest average operational efficiency followed by class 2 & class 3. Class 5 has the lowest average operational efficiency but high quality efficiency.

Though this set of efficient FQHCs had an average quality outputs greater than the target values, examining the individual efficient FQHCs, there are FQHCs that didn’t meet the quality output targets even though they have an acceptable quality efficiency which is a potential drawback with this approach.

Here's the summary on the efficient individual FQHCs resulted from the analysis that didn't meet the quality output targets.

1. 20 FQHCs didn't meet either one of the quality output targets.
2. 10 FQHCs didn't meet the quality access target
3. 16 FQHCs didn't meet the non-low birth weight births target

5.2.2 Partitioned S&L approach

In the partitioned S&L approach, DEA models are run for a set of FQHCs individually for the LCA classes obtained by LCA analysis. Solving DEA models individually for the LCA classes that considered the patient demographics and regional differences may better represent FQHC peer groups for comparison. Thresholds used in the aggregated S&L approach (QuEff_Initial=0.95) is also used in this partitioned S&L approach. The approach is similar to the approach in aggregated S&L method with an only change of running DEA models for individual classes.

The scatter plot graph below represents the efficiencies at the end of the iterative process

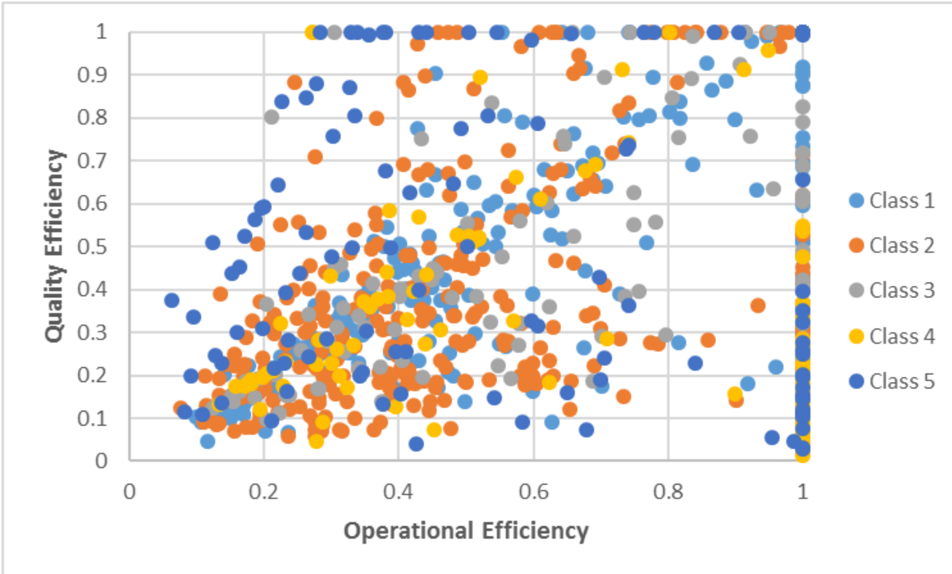

Figure 2. Operational Efficiency vs Quality Efficiency- Partitioned S&L method

313 FQHCs were removed from the iteration process as they had an operational efficiency of one and unacceptably low quality efficiency. 142 FQHCs were found to be efficient with an operational efficiency of one and quality efficiency above threshold. 41 were of class 1, 42 were of class 2, 28 were of class 3, 23 were of class 4 & 8 were of class 5. FQHCs found to be efficient in the aggregated S&L approach is also found to be efficient in the partitioned S&L approach.

The table below shows the summary statistics of operational & quality efficiencies at the end of iterative process by class

Class	Number of FQHCs	Operational Efficiency		Quality Efficiency	
		Mean	Std. Deviation	Mean	Std. Deviation
1	291	0.682	0.311	0.483	0.316
2	402	0.627	0.317	0.423	0.343
3	148	0.730	0.305	0.522	0.337
4	157	0.785	0.308	0.367	0.339
5	113	0.558	0.326	0.566	0.361
Total	**1111**	**0.670**	**0.320**	**0.458**	**0.341**

Table 6. Operational Efficiency and quality efficiency by class- Partitioned S&L method

In the partitioned approach, class 4 has the highest average operational efficiency similar to the results from the aggregated S&L approach and class 5 having the least operational efficiency with high quality efficiency.

FQHCs found to be efficient in the aggregated S&L method is also found to be efficient in the partitioned S&L method. These FQHCs were relatively smaller with an average of 5056 total annual patients. The average of the operational outputs of these efficient FQHCs is less than the average of the operational outputs of FQHCs within the class in the analysis. The efficient FQHCs found in this partitioned approach have an average quality outputs of 78.37% for quality access & 92.47% for non-low birth weight births which is greater than the quality output targets. Similar to the aggregated S&L approach, there are FQHCs which didn't meet the quality output targets but still found to be operationally efficient with quality efficiency above the threshold.

5.3 Quality Adjusted DEA approach by Sherman & Zhou

The potential drawback as mentioned with the S&L approach is that the quality outputs of few of the efficient FQHCs resulted in the analysis not meeting the quality targets. FQHCs has an accepted quality efficiency but still they haven't met any one of the quality output targets. To overcome this limitation as an alternative approach, quality adjusted DEA approach of Sherman and Zhu has been performed.

5.3.1 Aggregated S&Z approach

In this approach, DEA model is run over a set of FQHCs for production outputs and the operational efficiencies for the FQHCs are identified. We refer to this efficiencies as OpEff_Initial. Any FQHCs with an OpEff_Initial of one and that any one of the quality outputs not meeting the quality output targets were taken out of the sample and the DEA model is again run over a new set of FQHCs to determine the operational efficiencies. Quality thresholds identified in the aggregated S&L are used in this approach as quality output targets. This process continues until all the FQHCs in the efficient reference set for production outputs have the quality outputs greater than the targets. We refer to the efficiencies at the end of iterative process as QuEff_Final. The scatter plot graphs below represents the operational efficiencies over quality access & non low birth weight births

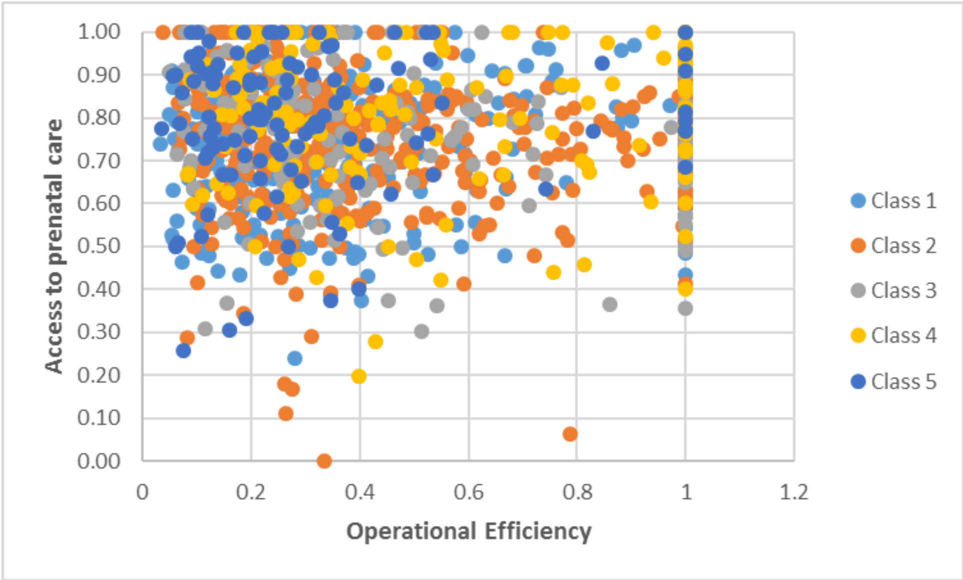

Figure 3. Operational Efficiency vs Access to prenatal care- Aggregated S&Z method

Figure 4. Operational Efficiency vs Non low birth weights- Aggregated S&Z method

82 FQHCs were removed from the iterative process which had an operational efficiency of one but didn't meet the quality targets.

The table below shows the summary statistics on the operational efficiencies determined by class in this aggregated S&Z approach.

Class	Number FQHCs	Operational Efficiency	
		Mean	Std. Deviation
1	291	0.381	0.282
2	402	0.462	0.297
3	148	0.46	0.309
4	157	0.521	0.312
5	113	0.31	0.245
Total	**1,111**	**0.433**	**0.298**

Table 7. Operational Efficiency by class- Aggregated S&Z method

Efficient FQHCs were found to be from all the different classes. 12 from class 1, 20 from class 2, 12 from class 3, 18 from class 4 and 7 from class 5. In the aggregated S&Z approach, class 4 has the highest average operational efficiency followed by class 2, 3, 1 and class 5 being the least which is similar to the results obtained in aggregated S&L approach. Regarding quality output of low birth weight index for the efficient FQHCs, class 1 is at 98.52%, class 2 is at 94.07%, class 3 is at 97.2%, class 4 is at 95.8% & class 5 is at 98.32%. Another quality output of access to prenatal care for the efficient FQHC, class 1 is at 88.8%, class 2 is at 77.6%, class 3 is at 79.10%, class 4 is at 79.7% & class 5 is at 83.5%. Average of the quality outputs of the all the efficient FQHCs is 81% for the quality access and 96.31% for the non-low birth weights which is more than the sample average of 76% for quality access & 91.6% for the low birth weight index.

With respect to the operational outputs, class 2 served an average of 2348 prenatal patients, class 3 served an average of 583, and class 4 served an average of 1159 which is more than the sample average of 483 prenatal patients. Average prenatal patient deliveries for class 2 is 1277, class 3 is 316, and class 4 is 678 which is more than sample average of 255 prenatal patient deliveries. All the efficient FQHCs served an average of 1137 prenatal patients which is more than the sample average of 483 prenatal patients. Average prenatal patient deliveries by the efficient FQHCs is 632 which is more than the sample average of 255 prenatal patients' deliveries. Unlike the aggregated S&L approach, the efficient FQHCs determined in this approach has both smaller and bigger size FQHCs. The average of the total annual patients visited these FQHCs is 26926 which is more than the sample's average used in the analysis.

5.3.2 Partitioned S&Z approach

Similar to the partitioned S&L approach of solving DEA models overs the set of FQHCs by each LCA class, we ran the quality adjusted DEA approach of Sherman & Zhu to the set of FQHCs by each class. The approach in determining the efficient reference set in aggregated S&Z method is followed here in partitioned S&Z approach as well.

The scatter plots graphs for the operational efficiency over quality access & non low birth weight births are below.

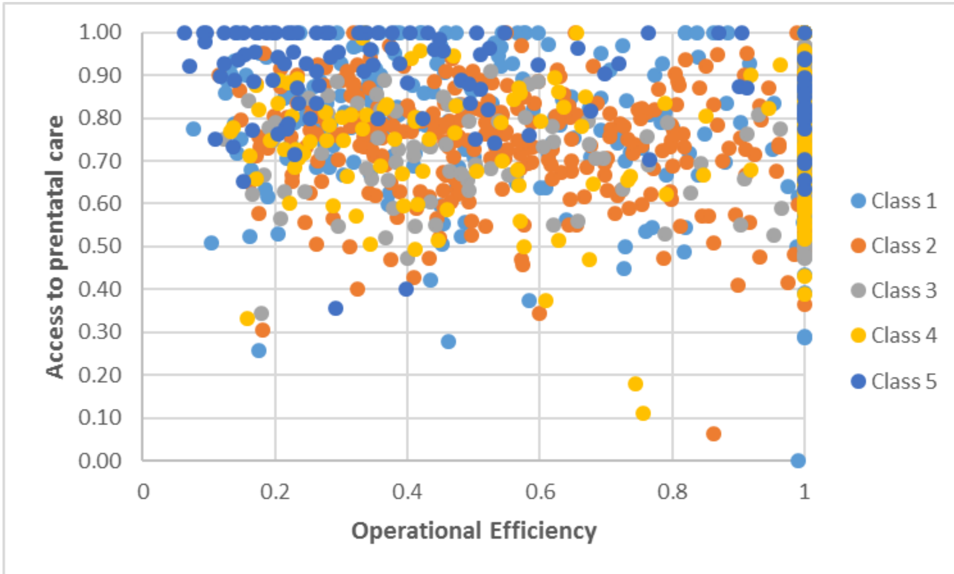

Figure 5. Operational Efficiency vs Access to prenatal care- Partitioned S&Z method

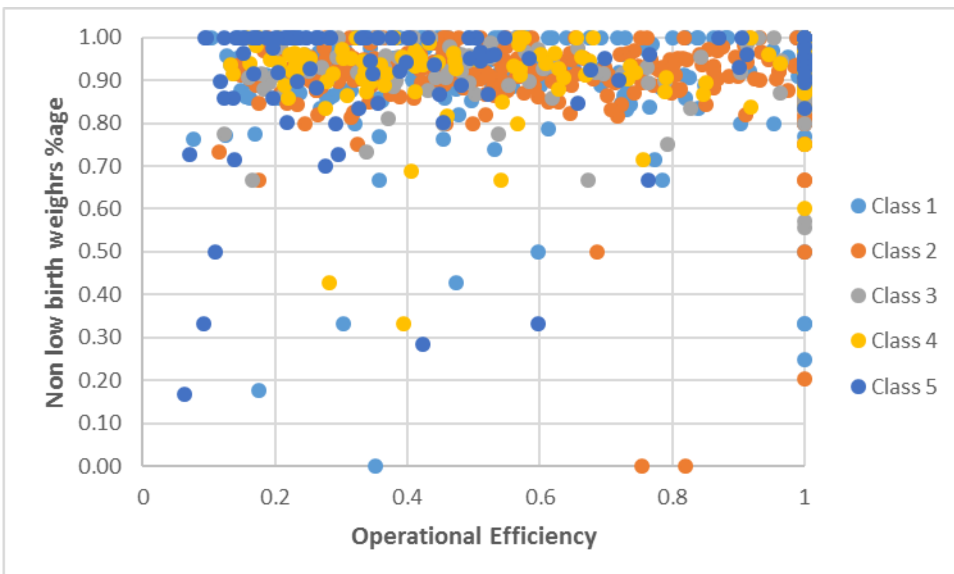

Figure 6. Operational Efficiency vs Non low birth weight – Partitioned S&Z method

205 FQHCs were taken off from the iterative process. 175 FQHCs were found to be efficient. 43 were of class 1, 53 were of class 2, 24 were of class 3, 39 were of class 4 & 16 were of class 5. In the partitioned S&Z approach, class 3 has the highest average operational efficiency followed by class 4, class 2, class 1 and class 5 being the least.

The table below shows the summary statistics on the operational efficiencies determined by class in this partitioned S&Z approach.

Class	**Number FQHCs**	**Operational Efficiency**	
		Mean	**Standard deviation**
1	291	0.658	0.305
2	402	0.679	0.279
3	148	0.722	0.301
4	157	0.700	0.316
5	113	0.472	0.32
Total	**1,111**	**0.661**	**0.305**

Table 8. Operational Efficiency by class – Partitioned S&Z approach

Regarding quality output of non-low birth weights for the efficient FQHCs, average non low birth weights for class 1 is at 97.1%, class 2 is at 96.2%, class 3 is at 97.7%, class 4 is at 95.5% & class 5 is at 96.2%. Another quality output of access to prenatal care for the efficient FQHCs, average of access to prenatal care for class 1 is at 86.5%, class 2 is at 80.6%, class 3 is at 82.4%, class 4 is at 82.1% & class 5 is at 84.3%. The average quality access of these efficient FQHCs is 83.02% and the average non low birth weight births is 96.50% which is more than the sample average of 76% for quality access & 91.6% for the low birth weight index.

With respect to the operational outputs, class 2 served an average of 1092 prenatal patients and class 4 served an average of 1114 which is more than the sample average of 483 prenatal patients. Average prenatal patient deliveries for class 2 is 584 and class 4 is 603 which is more than sample average of 255 prenatal patient deliveries. All the efficient FQHCs served an average of 725 prenatal patients which is more than the sample average of 483 prenatal patients. Average prenatal patient deliveries by the efficient FQHCs is 394 which is more than the sample average of 255 prenatal patients' deliveries. The average of the total annual patients visited these FQHCs is 20794 which is more than the sample's average used in the analysis.

Chapter 5. Conclusion

Efficiencies of the FQHCs are determined using the two-model DEA and quality adjusted DEA model. DEA model for the whole sample (aggregated approach) and the DEA model by class (partitioned approach) using LCA based on the regional and population measures is performed for both the models. Performing LCA on the FQHCs is helpful to determine the efficiency scores for the FQHCs as the FQHCs are compared against its own set of peers to reflect the efficiency scores. It was found that the efficient FQHCs determined in the S&L approach are smaller FQHCs. This is because the FQHCs used relatively less inputs to produce the outputs which makes them efficient relative to the other FQHCs in comparison. In terms of the operational outputs, the average prenatal patients and the prenatal patient's deliveries of the efficient FQHCs determined by the S&L approach is less than the sample average used in the analysis. One of the drawbacks with the S&L approach is that, there are FQHCs that are in the efficient reference set even without meeting the quality output targets which is the drawback of this S&L method. So, when using this method specifically in the health care industry, one must decide if this method is viable in decision making to determine the efficient FQHCs though they don't meet the quality output targets.

In the S&Z approach, we see that, 69 FQHCs that are efficient under aggregated S&Z approach is also efficient under partitioned S&Z approach. S&Z approach is found to be superior than the S&L approach. The efficient FQHCs are found to be both smaller and larger FQHCs unlike the S&L approach of just smaller FQHCs. In the S&Z approach the FQHCs found to be efficient have also met the quality output targets unlike the S&L approach of FQHCs being efficient but not meeting quality outputs. The partitioned approach of S&Z allowed many smaller FQHCs than the aggregated S&Z approach. The efficiency scores obtained in the partitioned S&Z approach is higher than the aggregated S&Z approach as in the partitioned approach because of the sample size in which the FQHCs are removed from the reference set and are replaced with less efficient FQHCs thus by increasing the efficiency score. But the same property couldn't be observed in the S&L approach. It is found that the efficiency scores decrease in partitioned S&L approach compared to the aggregated S&L approach as the S&L method doesn't necessarily remove FQHCs with high efficiency and low quality which is another limitation of the partitioned S&L approach. A major contribution in this research is, we performed LCA before performing DEA, thus FQHCs are compared only against their peer group.

References

1. Amico, P. R., Chilingerian, J. A., & van Hasselt, M. (2014). Community health center efficiency: the role of grant revenues in health center efficiency. Health Services Research, 49(2), 666-682.
2. Banker, R.D., Charnes, A., & Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
3. Charnes, A, Cooper, W.W., & Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 429-444.
4. Charnes, A, Cooper, W.W., & Rhodes, E. (1979). Short Communication: Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 339.
5. Charnes, A, Cooper, W.W., & Rhodes, E. (1981). Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through. *Management Science*, 27(6), 668-697.
6. Jose Manuel Cordero Ferrera, Eva Crespo Cebada, Luis R. Murillo Zamorano (2014). The effect of quality and socio-demographic variables on efficiency measures in primary health care. *European Journal of Economics, 15:289-302*
7. Javier Salinas- Jimenez, Peter Smith (1996). Data envelopment analysis applied to quality in primary health care. *Annals of Operations Research 141-161*
8. Kantayya VS, Lidvall SJ. Community health centers: disparities in health care in the United States 2010. *Dis Mon. 2010; 56:681-97*
9. Alexander GR, Korenbrot CC. The role of prenatal care in preventing low birth

weight. Future Child. 1995;5:103-20.

10. UDS Mapper. The American Academy of Family Physicians. 2017. www.udsmapper.org. Accessed 20 Jun 2017.

11. Dong- Shang Chang, Fu- Chiang Yang. A New Benchmarking Method to Adva

12. Centers for Medicare and Medicaid services. CMS Regional Offices. 2017. https://www.cms.gov/Medicare/Coding/ICD10/CMS-Regional-Offices.html. Accessed 19 Dec 2017.

13. Wade D. Cook, Karou Tone, Joe Zhu. Data Envelopment Analysis: Prior to choosing a model (2014). *Omega 44 1-4.*

14. Antonio Giuffrida & Hugh Gravelle. Measuring performance in primary care: econometric analysis and DEA (2001). *Applied Economics, 33:2, 163-175.*

15. Giuffrida A, Gravelle H. Measuring performance in primary care: econometric analysis and DEA. Appl Econ. 2001;33:163-75.

16. Blumenshine P, Egerter S, Barclay CJ, Cubbin C, Bravemen PA. Socioeconomic disparities in adverse birth outcomes: A systematic review. Am J Prev Med. 2010;39:263-72.

17. Dubay L, Joyce T, Kaestner R, Kenney GM. Changes in prenatal care timing and low birth weight by race and socioeconomic status: Implications for the Medicaid expansions for pregnant women. Health Serv Res. 2001;36:373-98.

18. Agrell P.J., Farsi M., Filippini M., & Koller M. (2013). Unobserved heterogeneous effects in the cost efficiency analysis of electricity distribution systems, CERETH Economics working papers series 13/171, CER-ETH - Center of Economic Research (CER-ETH) at ETH Zurich.

19. Centers for Disease Control. (2017). National Center for Health Statistics, Birthweight and Gestation, https://www.cdc.gov/nchs/fastats/birthweight.htm

20. Clogg, C.C. (1995) Latent class models: Recent developments and prospects for the future. In G. Arminger, C.C., Clogg, & M.W. Sobel (Eds), *Handbook of statistical modeling for the social and behavioral* sciences (Pp. 311-59.). New York, NY: Plenum Press.

21. Collins, L.M., & Lanza, S.T. (2010) *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. Hoboken, NJ: Wiley.

22. Emrouznejad, A., & Yang, G. L. (2017). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*.

23. Health Resources and Service Administration. (2015). 2015 Health Center Data – Health Center Program Grantee Data. Retrieved from https://bphc.hrsa.gov/uds/datacenter.aspx.

24. Health Resources and Service Administration (2017). FY 2017 Annual Performance Report. Available online at https://www.hrsa.gov/about/budget/fy17annualperformancereport.pdf

25. Huang, Y-G. L. and McLaughlin, C. P. (1989). Relative efficiency in rural primary health care: an application of data envelopment analysis, *Health Services Research, 24, 143-58*

26. Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health economics, 17*(10), 1107-1128.

27. Hollingsworth, B., Dawson, P. J., & Maniadakis, N. (1999). Efficiency measurement of health care: a review of non-parametric methods and applications. *Health care management science*, *2*(3), 161-172.

28. Marathe, S., Wan, T.T.H., Zhang, J., & Sherin, K. (2007) Factors influencing community health centers' efficiency: A latent growth curve modeling approach. Journal of Medical Systems, 31, 365-374.
29. Ozcan, Y. A. (2008). Health care benchmarking and performance evaluation. *An assessment using data envelopment analysis (DEA)*, 4.
30. Sherman, H.D., & Zhu, J. (2006). Benchmarking with quality-adjusted DEA (Q-DEA) to seek lower-cost high-quality service: evidence from a US bank application. *Annals of Operations Research*, 145(1), 301-319.
31. Shimshak, D., & Lenard, M.L. (2007). A two-model approach to measuring operating and quality efficiency with DEA. INFOR, 45(3), 143-151.
32. Worthington, A. C. (2004). Frontier efficiency measurement in health care: a review of empirical techniques and selected applications. *Medical care research and review*, *61*(2), 135-170.
33. Lazarsfeld, P.F., & Henry, N.W. (1968). Latent Structure Analysis, Boston, MA, USA: Houghton Mifflin.
34. Nyland, K.L., Asparouhov, T., & Muthén, B.O. (2007) Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14(4), 535-69.
35. Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. *Applied latent class analysis*, *11*, 89-106.