Fiscal and Economic Research Center

Technical Efficiency and Cost-Ratios of State Health Care

By

Russell D. Kashian, Ph.D.

Fiscal and Economic Research Center
University of Wisconsin-Whitewater
800 W. Main Street
Whitewater, WI 53190

Fall 2015

Staff Paper 14.5

Contributors

Russ Kashian, PhD
Primary Investigator
University of Wisconsin – Whitewater

Andrew Kueffer
Lead Researcher
University of North Carolina – Greensboro

Jeremy Peterson
Research Analyst
Marquette University

Derrek J. Grunfelder-McCrank
Economics and Finance Major
University of Wisconisin-Whitewater

Mary Cummings
Research Analyst
University of Wisconsin – Whitewater

Abstract:

This paper addresses how health care systems throughout our country compare to each other based on technical and cost efficiency. The efficiency of each state's health care system was determined by: (1) Measures of health care quality, general population health and insurance coverage are found in order to determine outputs of the health care systems along with input measures. Principal component analysis is used to attain some of the output variables by creating an index of component variables. (2) Then, on a state basis, technical efficiency is calculated to determine which states are most efficient at allocating inputs, which were capital and labor, in order to attain outputs, which were quality care, access and health outcomes. The states are then ranked by their technical efficiency for comparison. (3) Lastly, cost-ratios are calculated in order to determine how the three outputs compare based on the average premiums paid by the residents of states. By comparing Wisconsin's technical efficiency and cost-ratio rankings to other states, routes of improvement can be explored for the Wisconsin health care system.

Table of Contents

Technical Efficiency and Cost-Ratios of State Health Care

Executive Summary

The quality of Wisconsin's health care delivery system is well-documented and supported by national studies. In 2014, a federal Agency for Healthcare Research and Quality (AHRQ) study ranked Wisconsin as the third best state for health care quality in the nation. Equally impressive is that Wisconsin ranks third in the nation for health care efficiency.

In a research study supported by the Wisconsin Hospital Association, economist Russell Kashian, Ph.D., at the University of Wisconsin – Whitewater, found Wisconsin to be the third most efficient state in the country. Kashian used financial, technological, and human resources as his inputs with the outputs being health outcomes, quality and access to care. Over a five-year period of 2008-2012, the study found Wisconsin's health care delivery system uses resources more efficiently than all but two states, Hawaii and Iowa, and Wisconsin patients have better outcomes, are more satisfied with the care they receive and care is more accessible in all parts of the state compared to almost all other states.

Study Details

This analysis was designed to provide employers a better perspective on value to determine if the dollars they put toward health care provide a good return on their workforce investment in Wisconsin compared to other states.

Why is technical efficiency important? Efficiency influences cost, which means as efficiency increases, costs decrease. Since employers pay a portion of employee health premiums, improvement in how efficiently resources are used in a health care setting help to reduce overall costs. However, inputs such as cost are only half of the struggle in creating efficient health systems. Good health outcomes are an important component to efficiency to ensure that employees return to work and to their normal activities faster following a hospital visit. That reduces costs associated with absenteeism and creates a positive work environment.

Technical efficiency exists when the outputs of health care are maximized given the existing input. In simple terms, the goal is to get the maximum output from the resources that are already in use. To start the analysis, an acceptable comparison mechanism using data that was common to all 50 states was developed. There was also the recognition that health outcomes needed to capture both qualitative and quantitative measures of health. A health care quality index that combined 10 widely-accepted measures of patient satisfaction, as a means of measuring quality, along with data that measures access to health care and employee health outcomes was also developed. These were the three "outputs" that were used to measure results from investments in health care. The patient satisfaction factors included patient evaluation data related to hospital staff communications and responsiveness, room cleanliness, and overall happiness with the care received. Other factors included were health insurance coverage rates and life expectancy for patients being treated for chronic diseases.

To be efficient, the health care system must maximize these outputs using the health care inputs that then generate employee/patient health. For the purposes of this study, the labor and capital inputs were measured by health care employment as a percentage of total employment and the number of beds per 1,000 people in the state.

Wisconsin was the third most efficient state in the country. Wisconsin was also the third best state for producing high patient satisfaction, in making care accessible and in creating favorable health outcomes.

Technical Aspects of the Study

The Technical Efficiency and Cost-Ratios of State Health Care study was designed to give a comprehensive comparison of health care systems used by the different states. A survey was used to determine various measures of health care quality in order to create a health care quality index. The survey is part of a national intiative sponsored by the United States Department of Health and Human Services that addressed 10 quality measures of hospitals. Principal components analysis is used to create the indexes from these quality measures. This index along with other outputs and inputs are used to determine technical efficiency and cost-ratios for individual states. The scope of the study includes:

a. General population health for states
b. State health care quality
c. Indexes compiled from principal components
d. Technical efficiency of health care in states
e. Importance of addressing technical efficiency issues
f. Cost-ratios of input/output for health care in states
g. How states compare on various measures.
h. Methods to improve cost-ratios in the short and long run

State comparisons allow Wisconsin to develop methods to become more competitive in health care relative to other states. All of the results contained herein are relative between states.

Introduction

This study was designed to give a comprehensive comparison of state health care systems and to discern how the various state hospital systems rank in efficiency. In order to define health care quality among states, a survey was created that addressed 10 measures of hospital quality. From there, the method of principal components analysis was used to create an index from the quality measures. The index, along with other outputs and inputs, was then used to determine the technical efficiency and cost-ratios for individual states. While the results are relative to their specific state, this comparison allows Wisconsin to develop methods that will help to further improve their health care system and become an ever more forceful competitor to other states.

Since this report provides information on the technical efficiency of a state's hospitals, it is important to define what we mean by technical efficiency. Technical efficiency exists when the output of health care is maximized given existing inputs. In simpler terms, we're trying to get the most output from the resources that are already in place. The specific outputs are health care quality, health care access, and employee health outcomes; the goal is to maximize these outputs using the inputs of hospital beds per 1,000 people in the state and the percentage of the labor force working in the health care sector by state. This study uses an employer perspective because of the significant stake that employers have in the efficiency of the health care systems in the states. This stake is due in part to employers paying a significant portion of employee health care premiums, but also because a wide range of studies demonstrate that employee health is positively linked to productivity and work performance. For already existing or prospective businesses, the efficiency of health care can have a significant impact on their bottom line. This study will be helpful in terms of attracting entrepreneurs and corporations considering new operations or expansions within a particular state.

The data used in this report is from 2008-2012, taken from the Center for Disease Control's (CDC) Behavioral Risk Factor Surveillance Survey (BRFSS), which is collected annually. Health care inputs are measures of capital and labor. We used beds per 1,000 people per state annually as our measure of capital. The data on beds per 1,000 people was provided by the American Hospital Association. Another input used was an indicator of labor, for which the proportion of employees in the health care industry was used. Our labor data was obtained from the U.S. Census Bureau's American Community Survey. Two adjustments were made to the input data to better capture inputs into employee health: first, the inputs are corrected for the proportion of elders in each state/year and secondly, the percentage of employees is measured as full-time equivalents.

The results from the 3 output model on technical efficiency show Wisconsin ranking 3rd in 2012 and 3rd for the whole 2008-2012. In review, technical efficiency determines the relationship between the output (the combined index on quality of care) and the inputs provided. The initial three inputs are beds per 1,000 in population by state and the percentage of the labor force working in the health care sector by state. The outputs are 1) health care quality is measured using survey data on the quality of care collected by the Centers for Medicare and Medicaid Services, 2) health care access, and 3) employee health outcomes. In the three output model, the Charlson comorbidity measure of 10-year survival rates is used. Regarding cost-ratios, Wisconsin ranked 11th for 2012 and 11th for 2008-2012 in the 3 output model. The cost ratio measures the efficiency regarding the cost per unit of the three outcome index. The findings presented here regarding the technical efficiency of state health care systems are of palpable relevance. It confirms the results of previous studies; that inefficiencies do exist and warrant concern and action. This study does not suggest changes or specific improvements for increased efficiency but it does provide the foundation for constructive discussion and proactive planning.

Technical Efficiency of Health Care in the States: The Employer Perspective

Many factors influence economic development across and within states. Human and natural resources, communications and financial networks, infrastructure, education and the regulatory regime and fiscal policy are each of obvious relevance. This report focuses on one crucial factor: the technical efficiency of health care. The technical efficiency of health care is defined as the maximum potential output of health care relative to given inputs of labor and capital.

Why study efficiency?

The efficiency of health care can prove to be a major driver in terms of attracting or repelling entrepreneurs and corporations considering new operations or expansion within a particular state, given that 17.9% of U.S. GDP was devoted to health care expenditures as of 2012 (World Bank, n.d.). For existing or prospective businesses, the efficiency of health care can have a significant impact on their bottom line. On the one hand, more than two-thirds of employees (68.2%) are covered by employer-sponsored health insurance (Janicki, 2013) so expenditures on health insurance premiums for employees mainly fall either directly on the employer or indirectly as a deduction from wages and salaries paid; those funds are then used to purchase inputs. On the other hand, a variety of studies link the quality of health care and employee health to productivity, showing that:

- Workplace health and wellness initiatives can yield up to a 3-to-1 return on each dollar invested (Chapman, 2005; American College of Occupational and Environmental Medicine, 2009).
- The chronic disease, diabetes, is estimated to account for employee productivity losses in 2012 of $18.5 billion in lost productive capacity due to early mortality, $21.6 billion in losses due to disability-related inability to work, and $20.8 billion for reduced productivity while at work (American Diabetes Association, 2013).
- A study of depression and productivity among U.S. workers found losses of $31 billion per year, partly due to increased absenteeism, but mainly due to reduced performance while at work (Stewart, et al., 2003).
- Chronic conditions, such as arthritis, asthma, chronic obstructive pulmonary disease-emphysema, depression, and chronic headaches, are associated with significant reductions in performance while at work and significant increases in absenteeism (Wang, et al., 2003; Loeppke, et al., 2009).
- A 2005 study found poor health to have caused productivity losses of $27 billion annually due to reduced performance while at work and $48 billion due to absence for illness (Davis, 2005).

The burden on employers and benefits in terms of improved productivity are far from the only reasons to study the efficiency of health care since these are also related to the well-being of the entire populace. Nonetheless, the focus on inputs used, and their effectiveness in generating employee health is central to the success or failure of economic development at the state level.

Efficiency and Health Care

Economic theory includes two types of efficiency: technical and allocative. Technical efficiency is achieved when the output is maximized for a given set of inputs, such as labor, buildings, utilities, supplies and the like. Allocative efficiency occurs when, given technical efficiency, the mix of inputs reflects prices which minimize the total cost of the output. Stated differently, technical efficiency implies that resources are not being wasted, while allocative efficiency implies the optimal mix of inputs. This study focuses on technical efficiency, or the degree to which a state's health care system is or is not wasteful.

In 2008, the Agency for Healthcare Research and Quality released a study of health care efficiency measures, and located 158 relevant, peer-reviewed studies using U.S. data. Most studies (98) addressed hospital efficiency, and physical inputs (used to measure technical efficiency) were used more often than financial inputs (as in cost efficiency). In terms of outputs, while many specific measures were used (250 in total), "very few measures (4) included the outcomes of care such as mortality or improved functional status. In addition, none of the outputs explicitly accounted for the quality of service provided." The AQA (www.aqaalliance.org/about.htm) (2006) has also argued that efficiency studies should include indicators of health care quality. Both care outcomes and quality are used here.

Consideration of a broad spectrum of data relevant to efficiency suggests that the U.S. has one of the least efficient health care systems in the developed world (Kumar, Ghildayal, Shah, 2011). These studies are useful, particularly in terms of methodology, as a guide for analyzing efficiency across states within the U.S., although no prior study has performed this specific task. Babazono and Hillman (1994) used regression analysis to estimate the association between health care spending and health outcomes in Organization for Economic Cooperation and Development nations, and found no connection. That result was replicated for a larger sample of countries by Filmer and Pritchett (1999). Evans, Tandon, Murray and Lauer (2001) used stochastic frontier analysis to measure cost efficiency across 191 nations over five years, using health expenditures as the inputs and healthy life expectancy as the output. That study found an association between health care expenditures and health outcomes. More recently, Sinimole (2012) used data envelopment analysis to study health care efficiency in 180 nations, using health care expenditures as costs, and a variety of mortality rates and (separately) rates of immunization coverage as outputs.

Criteria for Measures

The measures of health care outputs and inputs are selected according to three criteria: 1) relevance to technical efficiency and to employers; 2) feasibility, here requiring annual data availability for 2008-2012 with regular updating; and, 3) the measures should be well-behaved. The first criterion follows from the purpose of the study, while the second follows from the time period selected for the study. For the third criterion, it is assumed that a system as large and complex as health care changes over time, but does not change quickly or dramatically from year to year. Given the time period encompasses the severe recession and on-going economic fragility

following the financial collapse of 2007, and will over time capture the effects of implementation of the Affordable Care Act, some change is expected. Nonetheless, substantial changes from one year to the next, such as a halving of inputs or a 30% improvement in health care quality within a particular state, are implausible. Stated differently, the third criterion requires some variation between states and over time within states, but not large within-state variation from year to year.

Outputs

Three types of outputs are used for this study: 1) health care quality, 2) health care access, and, 3) employee health outcomes.[1] The inclusion of measures of both quality and health outcomes is recommended by AHRQ (2008), while the restriction of the health outcomes measures to employees is consistent with a focus on efficiency from the vantage point of employers. Sinimole (2012) also uses health care access (there indicated by adult immunization rates) as an output of the health care system. Access can be viewed as incorporating partial outcomes in terms of either equitable distribution of health care or effective coverage (Smith, 2012). However, the rationale for including access in this study is simpler: once a measure of the quality of care provided is included as an outcome, that measure is not meaningful absent information on the proportion of individuals for whom care is or is not provided. The output measures are:

Health Care Quality Index:
The Centers for Medicare and Medicaid Services (2009-2013) collects survey data from approximately one million individuals each year following hospital discharge, including 24 items summarized as 10 quality measures. The topics covered range from the quality of communications with and the responsiveness of various hospital staff, pain and medicine management and information, the hospital environment, and the overall quality of the hospital. Using average state-level responses on the 10 quality measures for the years 2008-2012, standard methods were used to create a single scale from the measures. The resulting health care quality index includes eight of the measures that draw upon information from 21 of the original survey items. The scale has a Cronbach's α of .964, so it is reliable.

Health Insurance Coverage:
In March of each year, the Current Population Survey, administered by the U.S. Census (2006-2013), includes a supplement providing information on health insurance coverage, which is used here as a measure of health care access. The supplement has an annual sample size of approximately 100,000 adults, which is not large enough to provide reliable state-level estimates of coverage. As a reasonable alternative, results are reported for two-year rolling averages. Those estimates are used for this study with e.g., 2012 figures utilizing data from the 2011 and 2012 supplements.

---

1 The AHRQ (2013) reports on various health care outcomes that arguably represent technical inefficiency: inappropriate prescription medications, potentially avoidable hospitalizations and emergency department visits, emergency treatment for mental illness, substance abuse or dental conditions, excess avoidable hospitalizations, and perforated appendices. In each case, these outcomes either represent waste and hazard to patient health or unnecessary use of health care inputs where fewer inputs used for preventive care would have improved efficiency. Unfortunately, even if these measures were available at the state level, the latest data available are from 2009, so cannot be used for a study covering the year 2012.

Charlson Comorbidity Index:
The Centers for Disease Control and Prevention (2009-2013) provides data on the incidence of various chronic diseases through the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is an annual telephone survey, administered by the states, the District of Columbia, Guam, Puerto Rico, and the Virgin Islands (the latter three entities are excluded here). The sample size is reasonable, with a 2012 median state sample of 6,085, a minimum of 3,200 for the District of Columbia, and a maximum of 18,325 in Massachusetts. Restricting the sample to employees reduces the sample size by approximately one-half in each state, and all observations are weighted using a BRFSS-developed weight so respondents reflect characteristics of the population. In 2011 cell phone sampling was added, and it is reasonable to assume that BRFSS data reliability improved at that time and continues to improve.

To map information on chronic diseases into a single scale, the index developed by Charlson, et al. (1987) is used. The Charlson Comorbidity Index was designed to provide information to health professionals regarding the likely years of survival for a prospective patient of a particular age and with various chronic illnesses. The BRFSS provides information on as few as four chronic conditions in 2008 to as many as nine conditions in 2011 and 2012, so the index was standardized within each year prior to analysis (see Appendix 2 for a complete description). The Charlson Comorbidity Index is used as one indicator of employee health outcomes.

General Health Indicator:
Although arguably less objective than the index just described, an alternative measure of employee health outcomes is provided in the BRFSS data. This measure uses responses to a single question "Would you say that in general your health is," with five possible responses ranging from poor to excellent. These types of questions, while arguably somewhat subjective, have been found to be reliable and valid in earlier studies (e.g., DeSalvo, et al., 2006). As with the index just discussed, the General Health Indicator sample for analysis is limited to employee respondents to the BRFSS telephone surveys, and the responses are weighted to yield an annual average for each state and the District of Columbia.

Inputs

Beds:
The American Hospital Association (2014) conducts an annual survey and reports the number of hospital beds in community hospitals (accounting for around 2/3 of all beds) per 1,000 in population by state. Beds are used as the indicator of capital inputs, with population controlling for the size of the state.

Health Care Employment:
Data for the labor inputs are drawn from the annual American Community Survey data produced by the U.S. Census (Ruggles, et al., 2010), with employees in the health care industry (Ind codes 7970-8270), measured as a proportion of all employees in the state. To correct for differences in hours, employees inside and outside of the health care industry are given a weight of .5 if they work less than 35 hours in a usual work week, or 1 if they are full-time, and the population weight (perwt) is applied to generate the estimates.

To identify the health care inputs used to generate employee health, the inputs had to be corrected for those that applied to care for the elderly, who utilize an average of 36% of all health care resources (AHRQ, 2006). To make this correction, each input was separately, linearly regressed against the proportion of each state's population above 65 years of age. Both capital and labor were positively and significantly related to the elder proportion.[2] The input measures were then corrected by subtracting the coefficient times the elder proportion in each state for each year.

Means and standard deviations for each of the four potential outputs, and for the uncorrected and corrected input measures, are provided in Table 1.

Table 1: Descriptive Statistics

Variables	Mean	Standard Deviation
Outputs		
Healthcare Quality Index	561.03	26.10
Health Insurance Coverage	85.69	3.97
Charlson 10-year Survival (employees)	.9015	.025
General Health Indicator (employees)	2.745	.085
Inputs		
Beds (per 1,000 residents)	2.785	.861
Beds Corrected (control for elderly population)	1.385	.841
Healthcare Employment	.0997	.0140
Healthcare Employment Corrected (control for elderly population)	.0349	.0112

Building the Health Care Quality Index

The Centers for Medicare and Medicaid Services (CMS) provides annual figures for the states and the District of Columbia for 24 survey items[3] completed by individuals following hospital discharge. The 24 items are summarized as 10 quality measures, generally using "top-box" coding (i.e., the highest possible rating on the item is assigned a value of '1', with '0' assigned to less favorable responses). For the January 2012-December 2012 reporting period, 3,925 hospitals reported, with a target of 300 surveys per hospital per year, yielding an approximate annual sample size of over one million respondents.

Methods for creating the Health Care Quality Index generally follow Worthington and Whittaker's (2006) preferred approach, although a comparison of factor analyses using the under-standardized and standardized variables is provided given the utilization of panel data (see Greenaway-McGrevy, Han & Sul, 2012).

2 A quadratic specification was checked in each case, and did not add significant explanatory power to the regressions.

3 For a copy of the survey, see http://www.hcahpsonline.org/files/HCAHPS%20V9.0%20Appendix%20A%20-%20Mail%20Survey%20Materials%20(English)%20March%202014.pdf

For the data covering 2008-2012 (January-December), 51 annual observations are available on the 10 quality measures. The values have a potential range from 0 to 100, but the unstandardized means are grouped tightly, ranging from a low of 58.1 for Quietness of the Hospital Environment, to a high of 82.7 for Cleanliness of Hospital Environment. The minimum and maximum values range from 49 (Responsiveness of Hospital Staff) to 87 (Communication with Doctors). It is safe to conclude that neither extreme skewness nor extreme values are problematic in these data.

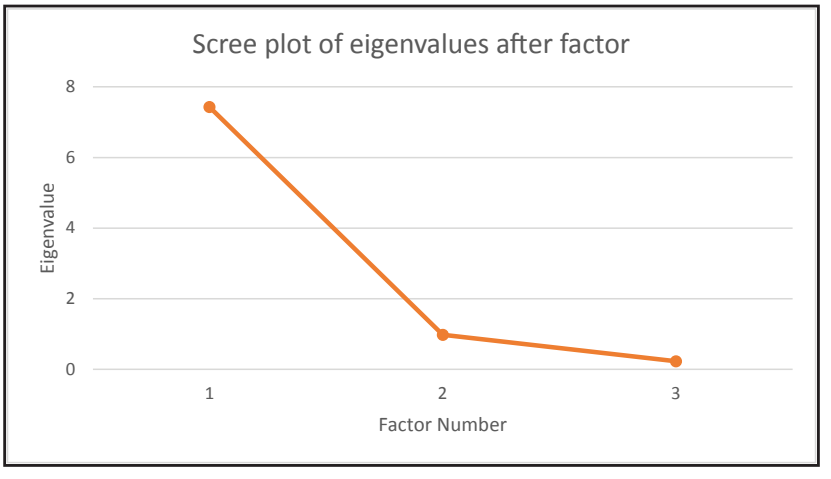
Principal components factor analysis of the non-standardized variables yields factor loadings as shown in Table 2. The loadings on Factor1 are all above the recommended level for scale inclusion of .6 (see Worthington and Whittaker, 2006), while only a single loading on Factor2 achieves that level. Only the Eigenvalue for Factor1 is above the standard Kaiser cut-off of one, with a value of 7.431. Horn's parallel analysis similarly yields a single Eigenvalue above one (7.278 for Factor1). These findings are consistent with the existence of a single underlying factor.

Table 2: Non-rotated Factor Loadings for Health Quality Index

Variable	Factor 1	Factor 2	Factor 3
Communication with Nurses	.950	.053	-.065
Communication with Doctors	.836	.411	.041
Responsiveness of Hospital Staff	.940	.000	-.205
Pain Management	.905	.124	.059
Communication about Medicines	.927	.021	.059
Cleanliness of Hospital Environment	.872	-.207	-.116
Quietness of Hospital Environment	.646	.604	.063
Discharge Information	.704	-.522	-.063
Overall Hospital Rating	.944	-.113	.211
Recommend the Hospital	.839	-.311	.283
Eigenvalues	7.431	.976	.229

However, loadings from the rotated factor matrix (not shown) yield only four above 0.6 for Factor1 and three values above 0.6 for Factor2, suggesting that two scales might be appropriate. Further, a scree plot of the Eigenvalues from the rotated factor matrix does not flatten after the first factor (see Figure 1), both of which are consistent with the existence of at least two underlying factors.

Figure 1: Scree plot of Eigenvalues



Replication of the factor analysis using the standardized variables (not shown) yielded evidence supporting a single factor. Only one Eigenvalue was above unity in the unrotated principal components analysis (at an identical 7.431), all factor loadings for Factor1 remained above 0.6, with only one above 0.6 for Factor2, and Horn's parallel analysis yielded a single adjusted Eigenvalue above unity (at 7.301). As recommended by Greenaway-McGrevy, Han and Sul (2012), the fewest number of factors with sufficient Eigenvalues from the analyses using the unstandardized and standardized variables are retained for further analysis.

The 10 items were therefore treated as a single scale and subjected to reliability analysis, yielding a Cronbach's α of 0.948, which is well above the traditional cut-off of 0.7. Items whose removal would improve the reliability were removed one at a time, causing the exclusion of Quietness of the Hospital Environment and Discharge Information variables. The remaining eight items yield a Cronbach's α of .964, and are added to create the Health Care Quality Index.

Building the Charlson Index of Comorbidity

The index developed by Charlson, et al. (1987) uses information on chronic illnesses to predict 10-year survival rates. As such, it provides an ideal mechanism for translating information on a variety of chronic illnesses found in the annual data from the Behavioral Risk Factor Surveillance System (BRFSS) into a single score reflecting the health of individual respondents. The scoring system assigns points to various conditions and age groups ('0' up to age 40, '1' age 41-50, '2' age 51-60, '3' age 61-70, '4' above 70). The summed value, *X*, is transformed as follows to obtain the 10-year survival rate, *10Year*:

$$Y = e^{(X-.9)}\text{, and} \qquad \text{(A1)}$$

$$10Year = .983^{Y}, \qquad \text{(A2)}$$

where *Y* is an intermediate estimate.

The conditions available in the data vary by year, with the name of each condition, points assigned, and availability by year are shown in Table 3. Note that the original scale used dementia (with '1' point) rather than a diagnosis of depression; the latter is assigned a value of 0.5 to reflect a less severe diagnosis and its relevance in a recent updating of the scale (Charlson, et al., 2008), which also included hypertension.

Table 3: Charlson Index Components

Condition	Index Points	Years Available
Myocardial infarction	2.0	2012-2008
Coronary heart disease	1.0	2012-2008
Stroke	1.0	2012-2008
COPD	1.0	2012-2011
Depression	0.5	2012-2008
Renal disease	1.0	2012-2011
Diabetes	1.0	2012-2011
Cancer other than skin	2.0	2012-2009
Rheumatic condition	1.0	2012-2011
Hypertension	1.0	2009

For each year, scale values are created for all BRFSS respondents who also report employment (typically around 190,000 respondents annually). The values are weighted by the population final weight in the BRFSS and then the mean value within each state is produced for use in the efficiency analysis. Note that, because the number of diseases covers ranges from a low of 4 in 2008 to a high of 9 in 2012, the results would artificially make individuals appear healthier in 2008 than in 2012. To control for the change in methods, annual mean scores for the 50 states plus the District of Columbia are adjusted to equal the 2012 mean.

Measuring the Technical Efficiency of Health Care

AHRQ (2008, Ch. 3) discusses a number of methods for measuring the efficiency of health care, including ratios, stochastic frontier analysis (SFA), and data envelopment analysis (DEA). Economists tend to use SFA, and that is used here (Battese & Coelli, 1995).

It is traditional and simple to posit that health care follows a Cobb-Douglas production function:

$$HC = AK\alpha L\beta \qquad (1)$$

where HC is the health care output, A is a constant, K is capital, L is labor, and the superscripts are the output elasticities of the inputs. Taking the natural log of (1) yields the equation to be estimated:

$$lnHC = A + \alpha(lnK) + \beta(lnY) \qquad (2)$$

To generate a single output variable, the four output measures were each standardized to mean zero, standard deviation one (with four added to each to ensure positive output values), which has the effect of weighting the outputs equally. Two variables are used to provide alternative estimates: one includes three outputs, including the health care quality index, health insurance coverage,

and the Charlson 10-year Survival, while the other includes those three plus the general health indicator. The three-output measure has the advantage of weighting quality, access and outcomes equally while the four-output measure places half of the weight on employee health outcomes, while downgrading the relative importance of quality and access. The prior fits the earlier theoretical discussion more cleanly, while the latter emphasizes technical efficiency as it affects employee health. The inputs are the corrected variables described in Table 1.

The model is estimated using the random effects estimator of Battese and Coelli (1995), which fits:

$$lnHC = A + \alpha(lnK) + \beta(lnY) - \mu_i + v_i \qquad (3)$$

where μ_i measures efficiency relative to the production frontier ($\mu_i > 0$), and v_i is a random error term. The method of Jondrow, et al. (1982) is used to measure efficiency, as is standard, and the estimates use the sfpanel files (Belotti, Daidone, Ilardi and Atella, 2013) and Stata 12.

Cost Index Analysis of Health Care

AHRQ discusses a number of methods for measuring the cost-ratio of health care, including ratios, stochastic frontier analysis (SFA), and data envelopment analysis (DEA)(2008, Ch. 3). For this analysis, we apply a variety of ratio measures of efficiency (i.e., outputs divided by inputs).[4] This is shown in equation (4):

$$Cost\ Ratio_{it} = \frac{hcqu_{it} + cha_{it} + hlin_{it}}{indprem_{it}} \qquad (4)$$

where $Cost\ Ratio_{it}$ is state *i*'s ratio of outputs to inputs in year *t*, $hcqu_{it}$ is state i's Health Care Quality Index in year *t*, cha_{it} is state *i*'s Charlson Comorbidity Index in year *t*, $hlin_{it}$ is the percentage of the population that has health insurance in state i during year *t*, and $indprem_{it}$ is the average individual health insurance premium of state *i*'s residents during year *t*. In appendices I-III, the measure of individual health insurance premium has been adjusted downward for employer contributions. The indexes used above have been discussed previously in the paper. What this cost ratio attempts to measure is the ratio of costs that are used inefficiently. For example, if a state has a cost ratio of 0.75, it means that 0.25 of all costs that state incurs in the health care industry are used inefficiently relative to the best practice competitor.

The change in the individual components of this cost ratio index is of great interest. For example, if the percentage of the population that had health insurance increased in a given state during a given year, the cost ratio would be expected to increase, indicating that the state had more productive usage of their costs, all else constant. The numerator of this index will not necessarily be changed "overnight," but the denominator could be.

4 Economists tend to use SFA, and we attempted to apply an SFA estimator with time-varying efficiency and random effects (Battese & Coelli, 1995) to a variety of cost efficiency specifications. However, the regressions failed to converge. The reason is that the inputs and outputs are not sufficiently positively correlated, which is not surprising given that SFA is requires all relevant inputs, and many of these are excluded as irrelevant to employers (for example, Medicaid and Medicare expenditures).

Technical Efficiency and Rankings Results

Results for the three-output technical efficiency estimates are presented in Table 4. Rankings and efficiency are provided for the latest year, 2012, and from an average of the results for all five years, 2008-2012. The rankings are from most efficient to least, meaning that the three-output model places Hawaii as most efficient in 2012. The efficiency numbers yield information on how much additional health care outputs could be provided through efficiency improvements, given the inputs deployed. So, for example, using the three-output model and 2012 results, Alabama, at 0.916 could increase its output of health care by an estimated 9.17% (i.e., 1/0.916) through efficiency improvements.

The time-varying character of the estimates is notable. Hawaii ranked '1' in 2012 under the three-output model, and '1' for the entire five year period under that same model. Less subtly, Delaware rises from a rank of '25' over the entire period to a rank of '11' in 2012 for the three-output model which means the efficiency of health care in that state actually improved over time, from an average of 0.876 for 2008-2012, to 0.924 in 2012. That increase, of less than 5%, may seem slight, but for a constant resource base, it represents a 5% improvement in each of the three output measures. Furthermore, the rank was vastly improved with the increased technical efficiency of the state.

See the figure below for a chart that gives a visual description of the top 20 states technical efficiency and health outcomes.

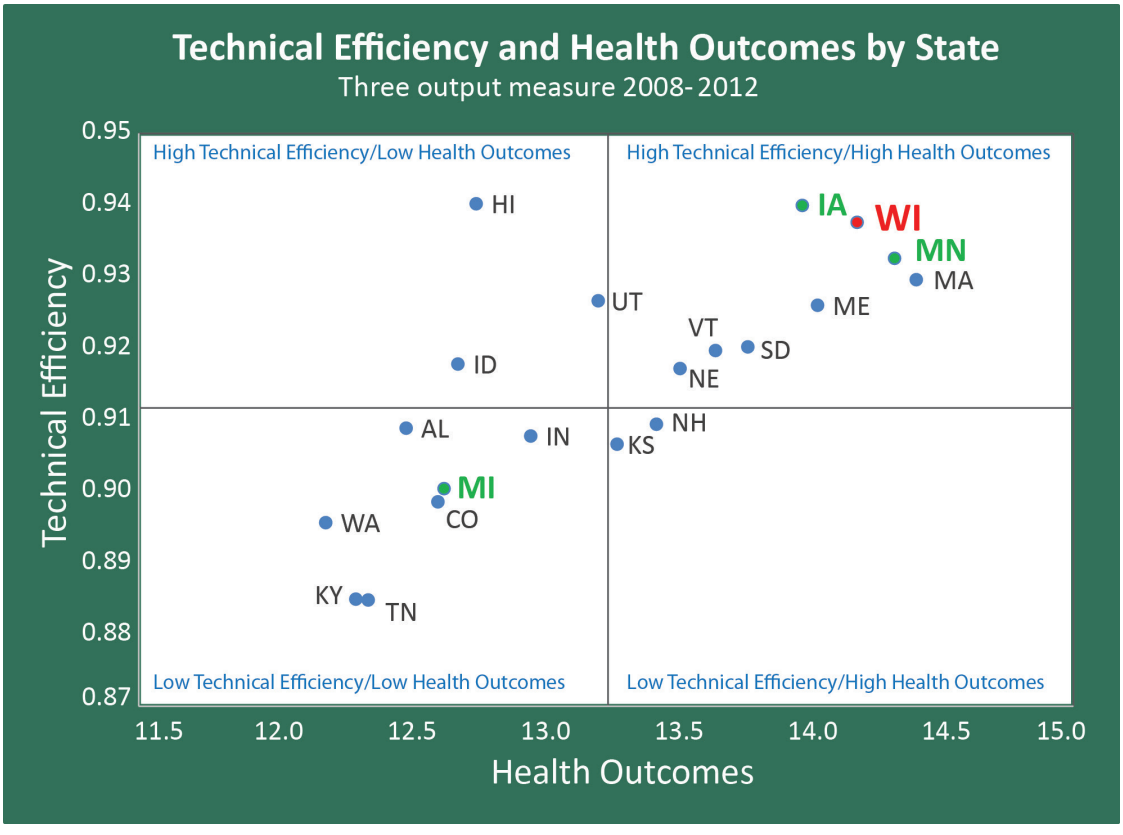


Table 4: Technical Efficiency Estimates and Rankings, 2012 and 2008-2012

State	3 Outputs			
	2012 Rank	2012 Efficiency	2008-2012 Rank	2008-2012 Efficiency
Alabama	16	0.916	13	0.909
Alaska	49	0.774	44	0.797
Arizona	38	0.864	42	0.831
Arkansas	36	0.865	38	0.849
California	42	0.829	45	0.787
Colorado	17	0.912	17	0.899
Connecticut	21	0.904	24	0.879
Delaware	11	0.924	25	0.876
District of Columbia	8	0.935	27	0.874
Florida	47	0.797	50	0.759
Georgia	41	0.850	40	0.844
Hawaii	1	0.975	1	0.940
Idaho	13	0.922	10	0.918
Illinois	26	0.896	32	0.864
Indiana	15	0.919	14	0.908
Iowa	2	0.949	2	0.940
Kansas	14	0.922	15	0.907
Kentucky	27	0.890	19	0.885
Louisiana	33	0.875	30	0.870
Maine	6	0.939	7	0.926
Maryland	46	0.800	43	0.797
Massachusetts	5	0.941	5	0.930
Michigan	10	0.925	16	0.900
Minnesota	4	0.944	4	0.933
Mississippi	31	0.883	37	0.853
Missouri	32	0.877	33	0.864
Montana	34	0.868	41	0.841
Nebraska	9	0.930	11	0.917
Nevada	51	0.728	49	0.764
New Hampshire	29	0.885	12	0.909
New Jersey	48	0.794	46	0.779
New Mexico	50	0.731	51	0.748
New York	44	0.814	48	0.767
North Carolina	30	0.885	26	0.876
North Dakota	37	0.864	34	0.863
Ohio	28	0.885	31	0.868
Oklahoma	40	0.856	28	0.872

State	3 Outputs			
	2012 Rank	2012 Efficiency	2008-2012 Rank	2008-2012 Efficiency
Oregon	23	0.898	22	0.880
Pennsylvania	35	0.867	36	0.862
Rhode Island	39	0.860	35	0.862
South Carolina	19	0.909	23	0.880
South Dakota	18	0.910	8	0.920
Tennessee	22	0.902	20	0.885
Texas	45	0.804	47	0.774
Utah	7	0.937	6	0.927
Vermont	12	0.924	9	0.920
Virginia	24	0.897	21	0.884
Washington	20	0.906	18	0.896
West Virginia	43	0.821	39	0.844
Wisconsin	3	0.947	3	0.938
Wyoming	25	0.897	29	0.871

Cost-ratio and Rankings Results

When using the Cost Ratio analysis we again use the 3 output model as described above. The specific outputs are health care quality, health care access, and employee health outcomes; the goal is to maximize these outputs using the inputs of hospital beds per 1,000 people in the state and the percentage of the labor force working in the health care sector by state. For the cost-ratio rankings, on average Kansas has the best 2008-2012 average. However, Iowa and Minnesota are also consistently in the top 5 rank for the 2008-2012 average periods. Wisconsin has a rank of 11 for 2012 in the three output model. Comparisons of 2012 to 2008-2012 cost-ratio model are the same for Wisconsin. This consistency between short and long-term results suggests that Wisconsin's results in these analyses are not "one off" events, but rather a trend that is ongoing. All of the results for the cost-ratios of states and their rankings are shown in Table 5.

Table 5: Cost-ratio and Rankings Results, 2012 and 2008-2012

State	3 Outputs			
	2012 Rank	2012 Efficiency	2008-2012 Rank	2008-2012 Efficiency
Alabama	10	0.759	7	0.783
Alaska	51	0.409	51	0.465
Arizona	36	0.628	39	0.610
Arkansas	9	0.761	12	0.752
California	43	0.552	46	0.551
Colorado	15	0.724	16	0.736
Connecticut	30	0.658	30	0.667

State	3 Outputs			
	2012 Rank	2012 Efficiency	2008-2012 Rank	2008-2012 Efficiency
Delaware	25	0.686	36	0.635
District of Columbia	34	0.635	45	0.561
Florida	47	0.543	50	0.509
Georgia	33	0.637	32	0.656
Hawaii	19	0.709	23	0.714
Idaho	2	0.849	8	0.778
Illinois	27	0.669	33	0.653
Indiana	23	0.701	19	0.729
Iowa	3	0.833	1	0.852
Kansas	1	0.860	4	0.809
Kentucky	28	0.662	17	0.735
Louisiana	31	0.655	22	0.719
Maine	21	0.705	21	0.728
Maryland	39	0.608	37	0.631
Massachusetts	13	0.744	9	0.763
Michigan	18	0.710	24	0.711
Minnesota	4	0.827	2	0.810
Mississippi	7	0.777	25	0.710
Missouri	22	0.704	18	0.734
Montana	46	0.544	42	0.589
Nebraska	5	0.811	6	0.802
Nevada	50	0.484	49	0.520
New Hampshire	26	0.672	27	0.700
New Jersey	49	0.527	48	0.543
New Mexico	42	0.572	44	0.569
New York	44	0.548	47	0.547
North Carolina	38	0.614	31	0.666
North Dakota	29	0.661	13	0.747
Ohio	12	0.751	10	0.755
Oklahoma	16	0.722	15	0.737
Oregon	41	0.601	38	0.611
Pennsylvania	32	0.655	29	0.669
Rhode Island	37	0.620	34	0.639
South Carolina	20	0.706	28	0.670
South Dakota	8	0.768	5	0.807
Tennessee	14	0.729	14	0.738
Texas	40	0.605	43	0.587
Utah	6	0.788	3	0.810
Vermont	17	0.713	20	0.729

State	3 Outputs			
	2012 Rank	2012 Efficiency	2008-2012 Rank	2008-2012 Efficiency
Virginia	24	0.697	26	0.707
Washington	35	0.631	35	0.638
West Virginia	48	0.529	40	0.607
Wisconsin	11	0.753	11	0.752
Wyoming	45	0.544	41	0.589

Discussion

Given the high cost and relative inefficiency of the U.S. health care system found in earlier studies, the findings presented here regarding the technical efficiency of health care systems across the states and the District of Columbia are of palpable relevance. The results are consistent with the results of earlier studies suggesting that inefficiencies exist, and warrant concern and action. What this study does not do is provide a roadmap to improving efficiency. Indeed, the sources of inefficiency are likely, in practice, to include many different causes (see AHRQ, 2013).

Finally, it is likely that many readers will focus on the rankings provided in Table 2. Those figures are easily interpreted, but also represent, by construction, a zero-sum game. There are numbers from '1' to '51', and efforts to improve efficiency, no matter how successful, will not add to or subtract from those numbers. What is instead of greater importance are the efficiency estimates, as these are constructed to allow for and reflect improvements over time.[5] One arena that will be of particular relevance here during the next few years is access, or health insurance coverage, as the Affordable Care Act may generate a dramatic increase in access. In terms of efficiency, including access as an output may appear to rig the results in favor of states that most effectively expand access, but that is not the case. Indeed, if expanded access is accompanied by additional resources, measured efficiency might even decline.[6] What is more certain is that all Americans have a stake in efficiency improvements in the health care system.

References

Agency for Healthcare Research and Quality (AHRQ). (2006). The high concentration of U.S. health care expenditures. Research in Action, 19. Accessed June 7, 2014 at http://www.ahrq.gov/research/findings/factsheets/costs/expriach/index.html

AHRQ. (2013). 2012 National Healthcare Disparities Report: Chapter 7. Efficiency. Agency for Healthcare Research and Quality, Rockville, MD. Accessed June 3, 2014 at http://www.ahrq.gov/research/findings/nhqrdr/nhdr12/chap7.html

5 This claim is not obvious, given the output measures were standardized at mean zero and standard deviation one, but standardization used data from all five years, thereby allowing for improvement or deterioration over time.

6 The arithmetic here is simple but counter-intuitive: if health insurance coverage expands by 10%, the health care output will expand by 3.3%. If capital and labor inputs also increase by 10%, measured efficiency will decline.

American College of Occupational and Environmental Medicine, Special Committee on Health, Productivity, and Disability Management. (2009). Health workforce/healthy economy: The role of health, productivity and disability management in addressing the nation's health care crisis. Elk Grove Village, IL: ACOEM. Accessed June 3, 2014 at http://www.acoem.org/uploadedFiles/Healthy_Workplaces_Now/Healthy%20Workforce%20-%20Healthy%20Economy.pdf

American Diabetes Association. (2013). Economic costs of diabetes in the U.S. in 2012. *Diabetes Care*, March 6, doi: 10.2337/dc12-2625

American Hospital Association. (2014). *AHA Hospital Statistics 2014 Edition*. Chicago, IL: AHA. http://www.ahadataviewer.com/book-cd-products/AHA-Statistics/

AQA. (2006). AQA principles of "efficiency measures." Accessed June 3, 2014 at http://www.aqaalliance.org/files/PrinciplesofEfficiencyMeasurementApril2006.doc

Babazono A, Hillman AL. (1994). A comparison of international health outcomes and health care spending. *International Journal of Technology Assessment and Health Care*, 10(3): 376-381.

Battese, GE, Coelli, TJ. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20: 325-332.

Belotti, F., Daidone, S., Ilardi, G., Atella, V. 2013. Stochastic frontier analysis using Stata. *Stata Journal*, 13: 719-758.

Centers for Disease Control and Prevention (CDC). (2009-2013). Behavioral Risk Factor Surveillance System, Annual Survey Data. Accessed May 28, 2014 at http://www.cdc.gov/brfss/annual_data/annual_data.htm

Centers for Medicare & Medicaid Services (2009-2013). Summary of HCAHPS Survey Results. Hachpsonline.org/HCAHPS_Executive_Insight [annual January-December discharges data]. Centers for Medicare & Medicaid Services, Baltimore MD. Accessed May 29, 2014 at http://www.hcahpsonline.org/SummaryAnalyses.aspx

Charlson, ME, Pompei, P, Ales, KL, et al. (1987). A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *Journal of Chronic Diseases*, 40(5): 373-383.

Charlson, ME, Charlson, RE, Peterson, JC, Marinopoulos, SS, Briggs, WM, Hollenberg, JP. (2008). The Charlson comorbidity index is adapted to predict costs of chronic disease in primary care patients. *Journal of Clinical Epidemiology*, 61(12): 1234-1240.

Chapman, LS. (2005) Meta-evaluation of worksite health promotion economic return studies: 2005 update. *American Journal of Health Promotion*, 19(6):1-11.

Davis, K, Collins, SR, Doty, MM, Ho, A, Holmgren, AL. (2005). Health and productivity among U.S. workers. Issue Brief #856, New York: Commonwealth Fund.

DeSalvo, KB, Fisher, WP, Tran, K, Bloser, N, Merrill, W, Peabody, J. (2006). Assessing measurement properties of two single-item general health measures. *Quality of Life Research*, 15(2): 191-201.

Evans, DB, Tandon, A, Murray, CJL, Lauer, JA. (2001). Comparative efficiency of national health systems: Cross national econometric analysis. *BMJ* paper, August. Accessed June 3, 2014 at http://www.bmj.com/content/323/7308/307

Filmer, D, Pritchett, L. (1999). The impact of public spending on health: Does money matter? *Social Science Medicine*, 49(10):1309-23.

Greenaway-McGrevy, R, Han, C, Sul, D. (2012). Standardization and estimation of the number of factors for panel data. *Journal of Economic Theory and Econometrics*, 23, 79-88.

Goetzel, RZ, Hawkins, K, Ozminkowski, RJ, Wang, S. (2003). The health and productivity cost burden of the "top 10" physical and mental health conditions affecting six large U.S. employers in 1999. *Journal of Occupational and Environmental Medicine*, 45(1): 5-14.

Janicki, H. (2013). Employment-based health insurance: 2010. Household Economic Studies, P70-134, U.S. Census Bureau. Accessed June 3, 2014 at http://www.census.gov/prod/2013pubs/p70-134.pdf

Jondrow, J., Lovell, C., Materov, I., Schmidt, P. 1982. On the estimation of technical efficiency in the stochastic production function model. *Journal of Econometrics*, 19: 233-238.

Kumar, S, Ghildayal, NS, Shah, RN. (2011). Examining quality and efficiency of the U.S. healthcare system. *International Journal of Health Care Quality Assurance*, 24(5): 366-388.

Loeppke, R, Taitel, M. Haufle, V, Parry, T, Kessler, RC, Jinnett, K. (2009). Health and productivity as a business strategy: A multiemployer study. *Journal of Occupational and Environmental Medicine*, 51(4): 411-428.

Lluis, S, Abraham, J. (2013). The wage-health insurance trade-off and worker selection: Evidence from the medical expenditure panel survey 1997 to 2006. *Industrial Relations*, 52(2): 541-581.

Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

Sinimole, KR. (2012). Evaluation of the efficiency of national health systems of the members of World Health Organization. *Leadership in Health Services*, 25(2): 139-150.

Smith, PC. (2012). What is the scope for health system efficiency gains and how can they be achieved? *Eurohealth*, 18(3): 3-6.

Stewart, WF, Ricci, JA, Chee, E, Hahn, SR, Morganstein, D. (2003). Cost of lost productive work time among U.S. workers with depresssion. *Journal of the American Medical Association*, 289(23): 3135-3144.

U.S. Census Bureau. (2006-2013). Current Population Survey. (2006-2013), "Number and Percentage of People Without Health Insurance Coverage by State Using 2- and 3-Year Averages," 2006 to 2013 Annual Social and Economic Supplements. Accessed May 29, 2014 at http://www.census.gov/hhes/www/hlthins/publications/reports.html

U.S. Treasury Department. (n.d.). Final regulations implementing employer shared responsibility under the affordable care act. Fact Sheet. Accessed June 4, 2014 at http://www.treasury.gov/press-center/press-releases/Documents/Fact%20Sheet%20021014.pdf

Wang, PS, Beck, A, Berglund, P, Leutzinger, JA, Pronk, N, Richling, D, Schenk, TW, Simon, G, Stang, P, Ustun, TB, Kessler, RC. (2003). Chronic medical conditions and work performance in the health and work performance questionnaire calibration surveys. *Journal of Occupational and Environmental Medicine*, 45(12): 1303-1311.

World Bank (n.d.). "Data, Health expenditure, total (% of GDP)," Washington, DC: World Bank. Accessed June 3, 2014 at http://data.worldbank.org/indicator/SH.XPD.TOTL.ZS

Worthington, RL, Whittaker, TA (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, 34, 806-838.